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Global sensitivity analysis reduces data collection efforts in LCA: A comparison between two additive manufacturing technologies

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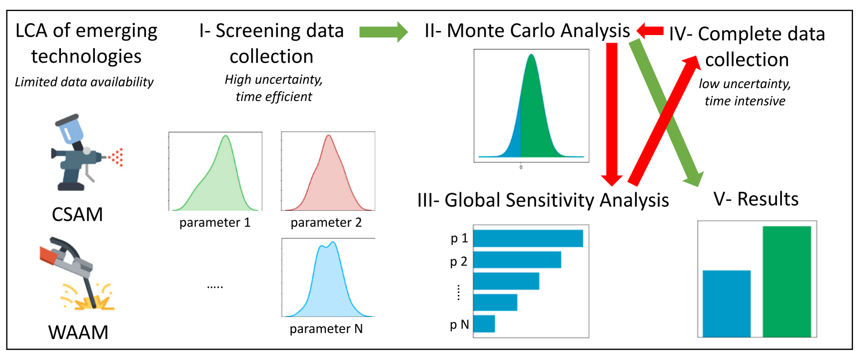
HIGHLIGHTS

- We proposed a framework to reduce data collection efforts in LCA.
- GSA is used to prioritize data collection of highly sensitive parameters.
- The framework was tested on a comparative additive manufacturing LCA.
- More works needs to be done defining the uncertainty and the convergence criterion.

GRAPHICAL ABSTRACT



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ABSTRACT

Accounting for the environmental impacts in the design of technologies is becoming a necessity for manufacturers. Life cycle assessment (LCA) is a well-established method to quantify the environmental impacts of products and services through a holistic perspective and is increasingly used to support the eco-design of products and technologies. However, LCA generally faces an inherent issue with data availability. Given the constraints on both time and cost for collecting inventory data to feed the LCA model, a trade-off between data cost robustness is required with an efficient data collection strategy. The objective of this study is to develop a framework to prioritize data collection efforts in LCA using uncertainty analysis. This starts with a screening life cycle inventory analysis systematically informing all input parameters with uncertainty ranges. Monte Carlo analysis is then used to propagate the uncertainty through the model. Stochastic results are then compared with an acceptable confidence level set by the decision maker. This is followed by a global sensitivity analysis using Sobol' indices to rank different input parameters based on their contribution to the variability of the results. This paves the way for an iterative process prioritizing further data collection focusing on the most sensitive parameters. A case study comparing cold spray and wire arc additive manufacturing illustrates how to

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operationalize the framework. Learnings from the case study highlight the importance of defining the uncertainty ranges and the convergence criterion, where more work is needed in that domain.

1. Introduction

Assessing the environmental impacts of products and services is becoming important for manufacturers, users and governments (Fernandez-Feijoo et al., 2014). Life cycle assessment (LCA) is a well-established method to quantify the environmental impacts of products and services in a holistic way (ISO, 2006), and is widely used by researchers and practitioners in the area of sustainability assessment (Finnveden et al., 2009). LCA is best suited for systems where sufficient information is available, as data collection is time intensive, especially in the inventory analysis phase (Laca et al., 2011; Zargar et al., 2022). The tool has an inherent problem with data availability due to several reasons. A typical product system includes thousands of processes that need to be described, and the high cost of primary data collection constrains the gathering of all the information (Reinhard et al., 2016). Some data is also not easily measurable or proprietary to manufacturers, and sharing this information could damage the competitive advantage of a company (Kuczenski et al., 2017). Regionalization is another aspect when collecting data, where the inventory for one process (e.g., electricity) is different according to the region (Mutel and Hellweg, 2009), and might require some proxies.

When assessing the environmental impacts of emerging technologies, data collection becomes even more challenging. The available data is usually for lab scale (e.g., for a prototype), and some proxies should be performed to account for the real scale dimensions, process synergies and industrial learnings (van der Hulst et al., 2020). Besides, most of the data is obtained from models for both the foreground data (e.g., extrapolating market scale operating conditions by technology learning curves (Bergesen and Suh, 2016)) and background data (e.g., integrated assessment models (Kaddoura et al., 2022)).

In an effort to overcome the data availability problem in LCA, and reduce time and cost associated with it, simplified versions of LCA were developed (Gradin and Björklund, 2021). Screening and streamlined LCAs are the most common simplification approaches used. Screening LCAs are qualitative or semi-quantitative LCAs mainly used at an early development stage (Ellingsen et al., 2016; Hochschorner and Finnveden, 2003). While the aim of those studies is to take a full life cycle approach, the impacts are not necessarily quantified, and hotspots are highlighted instead. Streamlined LCAs are quantitative yet simplified studies (Arena et al., 2013; Hung et al., 2020). Those methods do not use the full potential of LCA by eliminating some processes and impact categories and relying on lower data quality. They are helpful in early-stage prognosis studies, but the simplifications included increases the risk of shifting the environmental impacts across different life cycle stages and misguiding in the results. When a complete environmental profile is needed, those methods are not fit for purpose, and other ways to collect data in an efficient way are needed.

The main strategies used to model missing data in LCA can be classified into data-driven (e.g., artificial neural network), mechanistic (e.g., process simulation) and future inventory data (e.g., learning curves) approaches (Zargar et al., 2022). For data-driven methods, a limiting factor is the high domain knowledge requirement, particularly for those using machine learning models (ibid.). Another limitation is that missing data are estimated (e.g., estimating unit process data using similarity-based approach (Hou et al., 2018)), requiring having a training set of datasets, and for new technologies where it is not possible to have a proxy, it is not applicable. Mechanistic models are mainly applicable to chemical and biological processes, and the data uncertainty must be assessed separately (Zargar et al., 2022). Future inventory data modelling is performed in prospective LCA studies (e.g., by patent analysis (Spreafico et al., 2023)), but usually adds more variability and uncertainty to the results (Spreafico, 2024). Gathering costly primary data will remain essential in LCAs, as simplifications and estimates may not suffice. Given budget limitations, it is crucial to follow approaches that are easily used by LCA practitioners and applicable across all product systems to prioritize data collection.

Reinhard et al. (2019) applied a contribution-based method to prioritize data collection in LCI databases. The principle is also applicable to products, where the inputs are ranked based on their contribution to the impact score, and the approach is commonly used by LCA practitioners. However, contribution analysis can be limited by its reliance on existing data, which might be wrong or of low quality, and results could possibly overlook potential hotspots. Another approach is based on the expected benefits (in terms of reduced uncertainty) per cost of getting the data by combining the value of information (VOI) with LCA (Marchese et al., 2018). This approach, while accounting for the issue of data quality and uncertainty, demands information on the VOI, which themselves could be uncertain and costly. To overcome these challenges, uncertainty analysis offers a more comprehensive solution by accounting for the low quality of data through wider uncertainty ranges, and is less data intensive than the VOI approach, where no information on the cost of data is needed. Using the uncertainty of data to identify key issues for further investigation and reliability improvement has been suggested since the early days of LCA (Heijungs, 1996; Lo et al., 2005), but not widely adopted. This could be due to the perception of statistical approaches as complex by LCA experts, or the computational power needed at the time.

The main use of uncertainty analysis in LCA has been to assess the reliability of the results (Larsson Ivanov et al., 2019; Von Pfingsten et al., 2017; Zhai et al., 2021) and give more comprehensive information to decision-makers (Cao et al., 2019; Mendoza Beltran et al., 2018; Romero-Gámez et al., 2017). To take a more active approach and reduce the uncertainty by increasing the quality of data, a global sensitivity analysis (GSA) could be used. GSA has been adopted by LCA practitioners and is increasingly being used (e.g., implemented in Activity Browser (Cucurachi et al., 2021) and available in easy-to-use codes (Puy et al., 2022)). GSA is used after stochastic methods (e.g., Monte Carlo analysis) to propagate the uncertainty and estimate how much each input contributes to the model's output variance. GSA has been used in both the life cycle inventory (Groen et al., 2017; Jaxa-Rozen et al., 2021; Khang et al., 2017; Lacirignola et al., 2017; Zhao et al., 2021) and the life cycle impact assessment (Cucurachi et al., 2016) stages of the LCA. The goal of performing the GSA in those studies was to assess the robustness of the study, contribute to decision-making, and provide simplified calculation models based on highest contributing parameters (Lacirignola et al., 2017). Patouillard et al. (2019) proposed a methodology to help LCA practitioners prioritize data collection for regionalization in life cycle impact assessment (LCIA) based on GSA. They highlighted the importance of setting the acceptable level of uncertainty and defining the uncertainty of the inputs. In the context of life cycle inventory (LCI), there is a lack of clear documentation of using GSA to prioritize data collection with consistent terminology and clear directions, despite it being suggested in literature. This would allow for easier implementation and better communication of the results, and the validity of the approach could be assessed.

The aim of this study is to propose a framework based on GSA to prioritize data collection efforts in LCA and reach conclusive results at a given confidence level while efficiently minimizing the work efforts. A case study comparing two additive manufacturing technologies is also provided to operationalize and test the framework.

2. Methods and data

2.1. Framework

In our framework, we propose not to start with complete and almost *blind* data collection phase as in a traditional LCA, but with a screening data collection, followed by uncertainty analysis to identify where to prioritize the data collection efforts (Fig. 1). Chronometers are added at the steps where the time would change compared to a traditional LCA. Green shapes and arrows refer to revised steps based on the learnings of the study and are mentioned in the discussion later. The following subsections describe the details of each step in our framework.

2.1.1. Goal and scope definition

We define the goal and scope of the study as specified by ISO 14044 for a traditional LCA (ISO, 2006). In a comparative study between two product systems (A and B) where this framework is applicable, the acceptable level of discrimination between them needs to be defined in this step, which we refer to as the convergence criterion. The latter is initially defined as the percentage of times the impact scores of A is lower than that of B during a defined set of Monte Carlo simulations. This can be seen as the confidence level that product A has lower environmental performance than product B given the uncertainties in the inventory data. The convergence criterion is based on the level of risk decision makers are comfortable with and the allocated resources to conduct the LCA.

2.1.2. Screening data collection

In this step, we identify the input processes and parameters defining the studied products and collect available data with minimum effort and without detailed and costly exploration. We follow the definition of Gradin and Björklund (2021) where screening "is applied in the inventory analysis steps, usually covering the entire life cycle with lower data quality." This could also be referred to as "desk-based" data collection strategy, where existing data source (e.g., product declarations) are used and roughly adapted (e.g., by extrapolation) when needed (Hischier et al., 2014).

2.1.3. Completeness check

Our framework builds on including as much inventory flows of the system as possible at the beginning, even if their quality is low. As there might be some truncation in the screening data collection, some methods could be used to fill those gaps. This could be done using input-output tables, information from LCAs of similar products (i.e., proxies) and applying the law of mass conservation (Huijbregts et al., 2001). When a study is done in the context of an industry, it is easier to have a sense check with experts in the field to ensure that most of the flows are included.

2.1.4. Defining the uncertainty distribution

A probability distribution function is applied to define the variability of all identified input parameters. As this is meant to be an initial screening modelling, in absence of specific information we suggest using a uniform distribution, which only requires a lower and upper bound value. This information is usually readily available in literature or could be estimated by experts. When no information is available, we recommend applying conservative lower and upper bounds. We recommend setting the lower bound to half the value and the upper bound to its double as suggested by Finnveden and Lindfors (1998) and Hedbrant and Sörme (2001). Other simplified sensitivity ranges (e.g., ±10 %) might fail to highlight highly inaccurate input parameters with only modest influence (Huijbregts et al., 2001). Such default values,

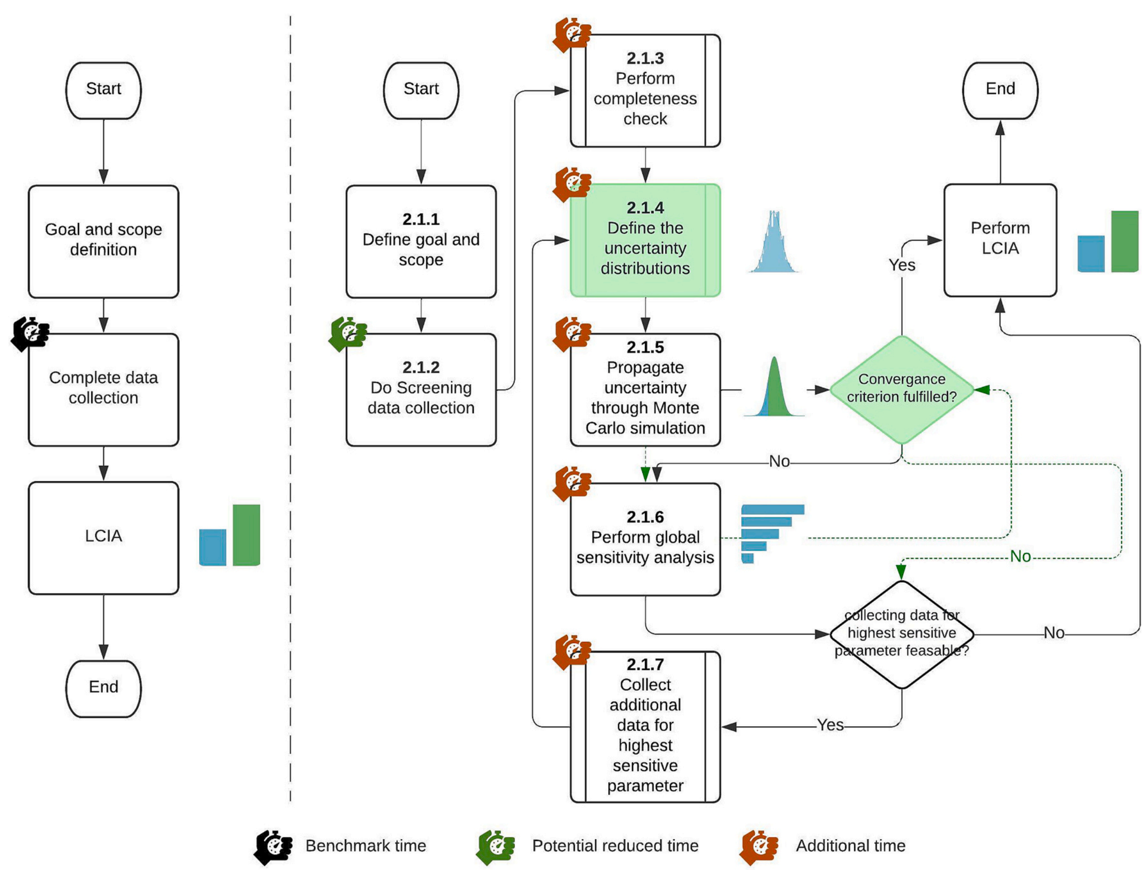

Fig. 1. Overview of the proposed framework (right) compared to a traditional LCA (left). Green shapes refer to steps that are revised and dashed green arrows are steps with altered order in the revised methodology.

however, should respect other limits of mass and energy conservation (e.g., not exceeding 100 % if dealing with percentages). Uncertainty distributions should also be defined for the background data, which is usually already provided in the database. In ecoinvent for example, lognormal distribution is used to estimate the uncertainties from qualitative assessments using a pedigree matrix (Ciroth et al., 2016). In our framework, we propose adding an additional uncertainty related to the discrepancy between the usually generic background dataset used (e.g., from ecoinvent) and the specific process used in the model. For example, the chromium steel dataset from ecoinvent comes with its own uncertainty irrespective of its use in a given LCA, and if this dataset is used as a rough proxy to represent a different specific steel alloy needed in the foreground of an LCA, this discrepancy further introduces uncertainty. We refer to this additional uncertainty as the *applicability uncertainty* and propose using pedigree matrices to quantify it as a starting point.

2.1.5. Uncertainty propagation through Monte Carlo simulation

A random sample of each input parameter is first generated (based on the defined mean, lower bound, and upper bound) and simultaneously propagated through the LCA model. We used 1000 Monte Carlo iterations for the case study below, but the number of iterations could be increased to obtain a representative frequency chart of the out variables. At each iteration, a value of the distribution of the parameter is chosen and used in the formula to get the distribution of the impact. Note that the same sampling of each parameter/process is used in calculating the LCA of A and the LCA of B and not independent sampling. For example, if steel is used in both A and B, the same impact of steel is allocated for A and B at each iteration. When all the iterations are done, we compare alternative A with B using a pairwise method, where the impact of each alternative is compared to the other for each Monte Carlo iteration. We represent this using Eq. (1) as suggested by Mendoza Beltran et al. (2018):

$$\%(GWP_A > GWP_B) = \frac{\#_{i=1}^{N}\left(GWP_{i,A} - GWP_{i,B} > 0\right)}{N} \times 100 \quad (1)$$

where # is a counting function and N is the number of iterations (1000 in our case). If the convergence criterion is achieved, the results of the LCA fulfill the objective of the LCA with no need to further iterate. Otherwise, more data collection will be required, and we move to the next step (Section 2.1.6).

2.1.6. Global sensitivity analysis

Further data collection specifically targets the parameter that contributes the most to the variability of the impact score. We suggest using the first order Sobol' indices (Sobol, 2001) that calculate quantitative indices allowing to rank the influence of each input parameter on the LCA results. We only consider the first order Sobol' index in this study assuming that the parameters are independent, but higher order Sobol' indices should be calculated when input parameters are correlated (Kevin Sinisterra-Solís et al., 2024; Wei et al., 2015). The GWP impact (or other impact categories) could be expressed as a function of different parameters as $GWP = f(p_1,p_2, \ldots,p_n)$. For a parameter p_i, the first order Sobol' index (SI_i) is calculated based on Eq. (2) as defined by Li and Mahadevan (2016):

$$SI_i = \frac{V[E[GWP|p_i]]}{V[GWP]} \quad (2)$$

where V is the variance and E is the expected value, both calculated based on the Monte Carlo results. More information on how the first order Sobol' index was calculated is available in Supplementary material 1.

2.1.7. Additional data collection

Data collection will focus on the input parameter identified as the most contributor to the variability based on the GSA. But first, we should check if we have access to the data or if it is feasible to collect it within the allocated resources (e.g., from a budget and time constraints). If it is not feasible to collect higher quality data for the parameter/process with the highest SI, the parameter/process has to be flagged, and we move on to the parameter with the next highest SI. Otherwise, more accurate data need to be collected by e.g., lab experiments (Hischier et al., 2014), running process simulations (e.g., using ASPEN PLUS) (Ferdous et al., 2024), experts' interviews, or further literature review. This is referred to as the "lab-based" data collection strategy (Hischier et al., 2014). Using the updated data, we go back to step 2.1.4.

2.2. Case study of emerging surface engineering technology

To demonstrate the applicability of the suggested framework, a case study was carried out on two additive manufacturing technologies.

2.2.1. Goal and scope definition

The aim of the study is to compare the environmental impacts of cold spray additive manufacturing (CSAM) and wire arc additive manufacturing (WAAM) at a 95 % confidence level. As no specific additively manufactured product is assessed, this study is a cradle to gate study, where the use and end-of-life phases are excluded. The transportation is also excluded for simplicity. The functional unit is mass-based and defined as "manufacturing 1 kg of an additively manufactured ring steel component in Quebec, Canada in 2022". The system boundaries associated with the functional unit is described in Section 2.2.4. The modelling is done using a code written in Python and available on Github (https://github.com/mohamadkaddoura/GSAPDaC), with input data provided in Supplementary material 2. The background data is based on the ecoinvent 3.8 database (Wernet et al., 2016) characterized by the IPCC 2013 global warming potential 100 years (GWP100a) characterization factors (IPCC, 2014). Other impact categories could be assessed by the framework, but only global warming potential is used here to demonstrate the applicability of the framework.

2.2.2. Screening data collection

The initial data was sourced from literature, where parameters relevant to each technology were determined. For WAAM, the inputs to the system are the welding wire (steel), shielding gas (argon), and electricity (in QC). The inputs for CSAM are feedstock powder (steel), carrier gas (nitrogen) and electricity (in QC). As the processes for powder production (atomization and annealing) are not available in ecoinvent, their parameters were included as well (Table 1).

2.2.3. Completeness check

Completeness check was done by discussing with domain experts in the industry, mainly from Polycontrols, a CSAM company in Canada. They confirmed that we included the main parameters, but also identified two missing parameters: the deposition efficiency and the post-processing losses. Both could have significant impacts on the results by affecting the electricity and gas supply, and the amount of feedstock needed that would be highly underestimated if we neglect those parameters. In fact, most of the losses of the material in thermal spray applications occur during the deposition phase due to low deposition efficiencies (Kaddoura et al., 2024). The values for those parameters were estimated with the help of experts and shown in Table 2.

Based on the collected parameters, the intermediary parameters (AM duration) and the processes (amount of material, gas, and electricity) are calculated according to the formulas given in Table 3. A parametrized model adds flexibility to the LCA (e.g., can change one parameter affecting a process rather than the amount of the process) and makes the data collection more precise and targeted. It would also allow to pinpoint exactly which parameter is contributing to the uncertainty.

2.2.4. Defining the uncertainty distribution

The identified parameters (Tables 1 and 2) were modelled with

Table 1
The parameters used to model CSAM and WAAM.

Parameter	Name	Amount	Unit	Source
Wire arc				
Wire feed	wire_fr	1.5	kg/h	(Bekker and Verlinden, 2018; Shah et al., 2023)
Shield gas flow rate	shi_gas_fr	15	L/min	(G.P. et al., 2017)
Wire arc power	power_wa	1.146	kW	(G.P. et al., 2017)
Casting losses	cast_loss	10	%	(Bekker and Verlinden, 2018)
Rolling losses	roll_loss	5	%	(Bekker and Verlinden, 2018)
Wire drawing losses	draw_loss	8	%	(Bekker and Verlinden, 2018)
Cold spray				
Powder feed rate	powder_fr	9	kg/h	(Vuoristo, 2014)
Carrier gas flow rate	car_gas_fr	1.675	m^3/min	(Vuoristo, 2014)
Cold spray power	power_cs	32	kW	(Vuoristo, 2014)
Atomization electricity	elec_atom	0.75	kWh/kg	(Lavery et al., 2013)
Atomization gas	arg_atom	0.333	kg/kg	(Lavery et al., 2013)
Atomization losses	atom_loss	5	%	(Lavery et al., 2013)
Annealing heat	heat_anneal	0.143	MJ/kg	(L et al., 2020)
Annealing losses	anneal_loss	0	%	(L et al., 2020)

Table 2
Additional parameters needed in the model.

Parameter	Name	Amount	Unit
Wire arc			
Deposition efficiency	dep_eff_wa	85	%
Cold spray			
Deposition efficiency	dep_eff_cs	90	%
General			
Post-processing losses	post_proc_loss	10	%

uniform pdfs as only the minimum and maximum values were found in literature (Table 4). For the shield gas flow rate, weld arc power, and post processing losses, no ranges were found, and the minimum and maximum were estimated as half and double the values to be as broad as possible. The deposition efficiencies' ranges were missing as well, but as identified by experts, both additive manufacturing technologies are highly efficient, and the range was defined accordingly. Throughout the paper, results relating to those parameters uncertainties will be colored blue. The uncertainty of the background processes was obtained directly from the ecoinvent database as based on the lognormal distribution generated by the pedigree matrix of the corresponding input processes. Those are colored orange in the following section. The applicability uncertainty distribution was modelled based on the pedigree matrix approach (Table S2 in Supplementary material 1) and are colored green in the paper. The resulting pdfs are available in Supplementary material 1 (Figs. S2 and S3).

Fig. 2 illustrates how different uncertainty distributions are applied across the different life cycle stages of CSAM. The orange boxes are the uncertainties based on the background data (pedigree matrix in ecoinvent). The green boxes represent the applicability uncertainty, which act as a scaling factor, and its distribution is based on our defined pedigree scores. Blue boxes are the foreground data, where the parameters affecting the input are shown, and are modelled using a uniform distribution as described earlier. The flow diagram for WAAM is available in Supplementary material 1 (Fig. S1).

3. Results

The results of the case study are presented hereby applying step by step the developed framework.

3.1. First iteration

Deterministic comparative LCA results showed that WAAM has a higher impact score (Global Warming Potential, GWP) than CSAM (2.44 and 1.71 kg CO_2-eq/f.u., respectively). More information about the deterministic results is available in Fig. S5 in the Supplementary material 1, as the focus of this study is on the probabilistic ones. Fig. 3 (a) plots 1000 Monte Carlo iterations for the difference between the impact of WAAM and CSAM (GWP_{WAAM}-GWP_{CSAM}). Stochastic results showed a likelihood that GWP_{WAAM} was higher than GWP_{CSAM} in 93.6 % of the runs (where the difference is positive). Since it is less than the convergence criterion defined in the goal and scope (95 %), more data was needed to be collected to refine the results. To understand where the variability comes from, a GSA based on the first order Sobol' indices was performed (Fig. 3, b) for the parameters (blue), background technology

Table 4
The minimum and maximum of the uniform distribution for different parameters.

Parameter	min	max	Source
wire_fr	1	2	(Bekker and Verlinden, 2018; Shah et al., 2023)
shi_gas_fr	7.5	30	estimated
power_wa	0.57	2.3	estimated
powder_fr	4.5	13.5	(Vuoristo, 2014)
car_gas_fr	0.85	2.5	(Vuoristo, 2014)
power_cs	17	47	(Vuoristo, 2014)
dep_eff_wa	0.8	1	estimated
dep_eff_cs	0.8	1	estimated
post_proc_loss	0.05	0.2	estimated

Table 3
Formulas to calculate the amount of processes needed based on the defined parameters, where density_ar = 1.63 g/L, density_n = 3.1293 kg/m3 and coating_amount = 1 kg (based on the functional unit).

Parameter/process	Name	Formula	Unit
WAAM duration	duration_wa	$\frac{coating\_amount}{wire\_fr}$	hrs
CSAM duration	duration_cs	$\frac{coating\_amount}{powder\_fr}$	hrs
Wire	wire	$\frac{coating\_amount}{(1-cast\_loss)\times(1-roll\_loss)\times(1-draw\_loss)\times dep\_eff\_wa\times\left(1-post\_proc\_loss\right)}$	kg
Powder	powder	$\frac{coating\_amount}{(1-atom\_loss)\times(1-anneal\_loss)\times dep\_eff\_cs\times\left(1-post\_proc\_loss\right)}$	kg
Electricity for WA	elec_wa	$power\_wa\times duration\_wa$	kWh
Electricity for CS	elec_cs	$power\_cs\times duration\_cs$	kWh
Argon	arg_wa	$\frac{shi\_gas\_fr\times duration\_wa\times 60\times density\_ar}{1000}$	kg
Nitrogen	nit_cs	$car\_gas\_fr\times duration\_cs\times 60\times density\_n$	kg

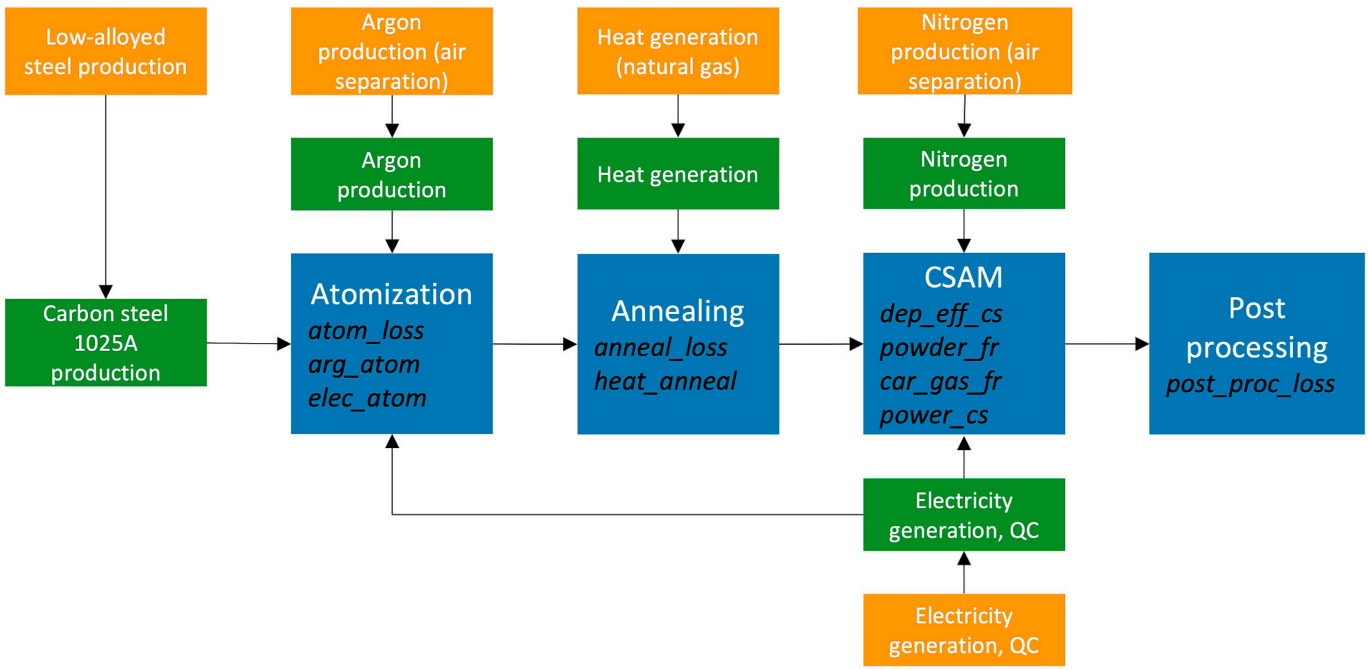

Fig. 2. Flow chart showing where different uncertainties originate from. Blue boxes represent foreground data, green boxes applicability and orange boxes background data. CSAM: Cold Spray Additive Manufacturing, QC: Quebec.

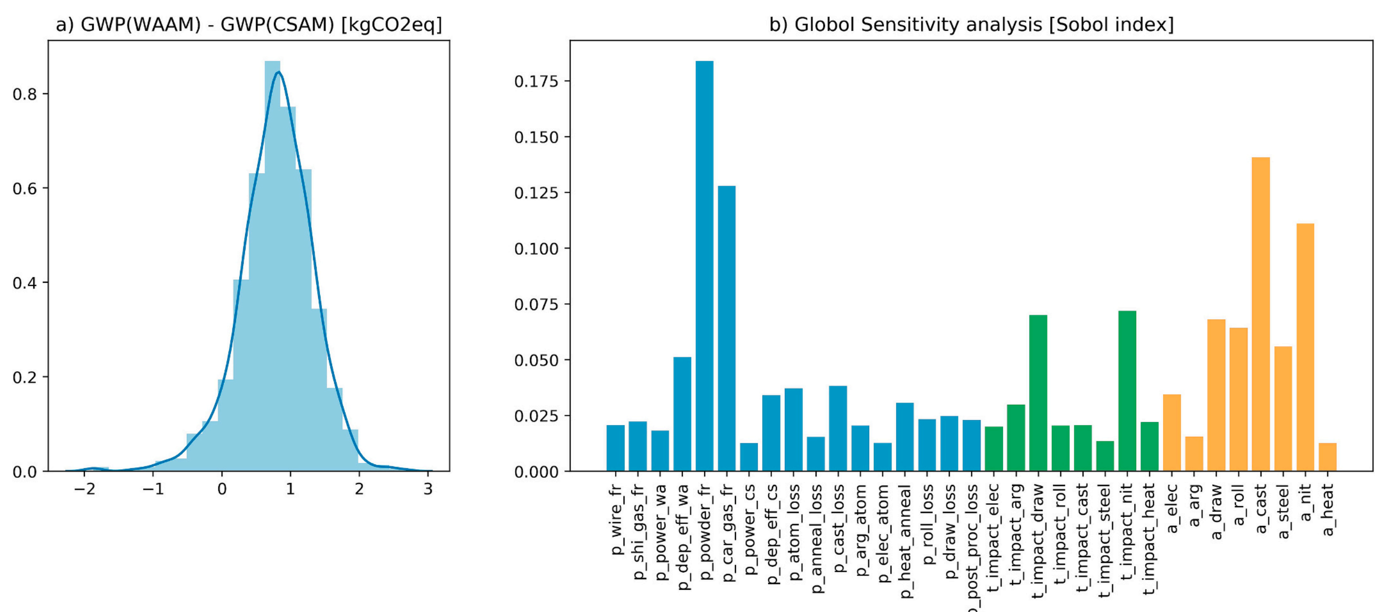

Fig. 3. The results of the first iteration of the a) Monte Carlo analysis and b) Global Sensitivity Analysis. Blue bars are for parameters, green bars for technology (background processes) and orange bars are for applicability.

flows (green), and applicability of the background technology flows (orange). The powder feed rate for the CSAM had the highest Sobol' index (0.18).

3.2. Second iteration

In this second iteration, targeted primary data were collected from Polycontrols for powder feed rate (1.5 kg/h uniformly distributed between 1.2 and 1.8). Updated results reversed the conclusion; GWP_{WAAM} became lower than GWP_{CSAM} for 98.1 % of the runs (Fig. 4, a). This shift is explained by a significantly lower feed rate value from measured data collected at the company compared to the initial data gathered from literature. A lower feed rate (less amount of powder deposited per hour) requires more electricity to deposit the same amount of powder, thus increasing the impact of CSAM. This can be seen from Table 3, where the CSAM duration is inversely proportional to the powder feed rate, and the electricity required for CSAM is directly proportional with the duration. The likelihood that GWP_{WAAM} is lower than GWP_{CSAM} (98.1 %) was greater than the defined convergence criterion of 95 %, suggesting that the results are conclusive. However, the carrier gas feed rate became the parameter contributing the most to the variability of the impact scores, with a first order Sobol' index of 0.35, >10 times higher than the others (Fig. 4, b). According to the initial framework, the iteration should stop at this step. But as an exploratory phase, a third data collection round

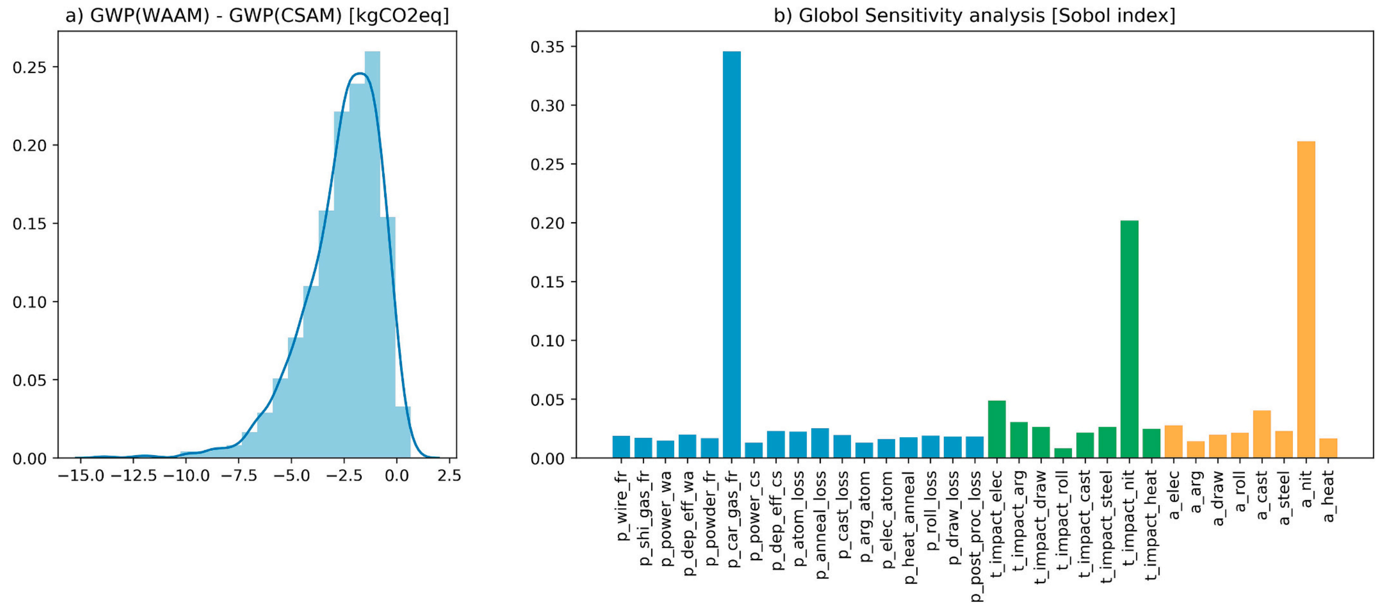

Fig. 4. The results of the second iteration of the a) Monte Carlo analysis and b) Global Sensitivity Analysis. Blue bars are for parameters, green bars for technology (background processes) and orange bars are for applicability.

was performed to check if the results of the Monte Carlo simulations were generating an adequate convergence criterion, or an early stop would lead to unreliable conclusions.

3.3. *Third iteration*

In this third iteration, primary data for the carrier gas flow rate were collected at Polycontrols (0.175 m^3/min uniformly distributed between 0.15 and 0.2) Updated results reversed the conclusion again; GWP_{WAAM} became higher than GWP_{CSAM} with a likelihood of 92.4 % (Fig. 5, a). This third iteration reduced the uncertainty range for the carrier gas flow rate by decreasing the upper and lower bound, meaning that less nitrogen is needed for the same duration of deposition and ultimately reducing the impact scores of CSAM. Since 92.4 % was lower than the convergence criterion, additional data collection was needed. The steel casting applicability had the highest Sobol' index after this iteration at around 0.2 (Fig. 5, b). However, because it corresponds to a background data (aluminum casting was used as a proxy), adjusting that flow to reflect the steel industry was out of allocated resources to this study, despite its importance. According to the framework, we focused the data collection on the parameter with the next highest Sobol' index, which is the power used for cold spray.

3.4. *Final iteration*

In the fourth iteration, primary data collection at Polycontrols was performed for the power used for the cold spray deposition (80.35 kW uniformly distributed between 43.05 and 106.85). The GWP_{WAAM} became lower than GWP_{CSAM} with a likelihood of 60.4 % (Fig. 6, a). At this point, the Sobol' indices for all the parameters were <0.1 (Fig. 6, b).

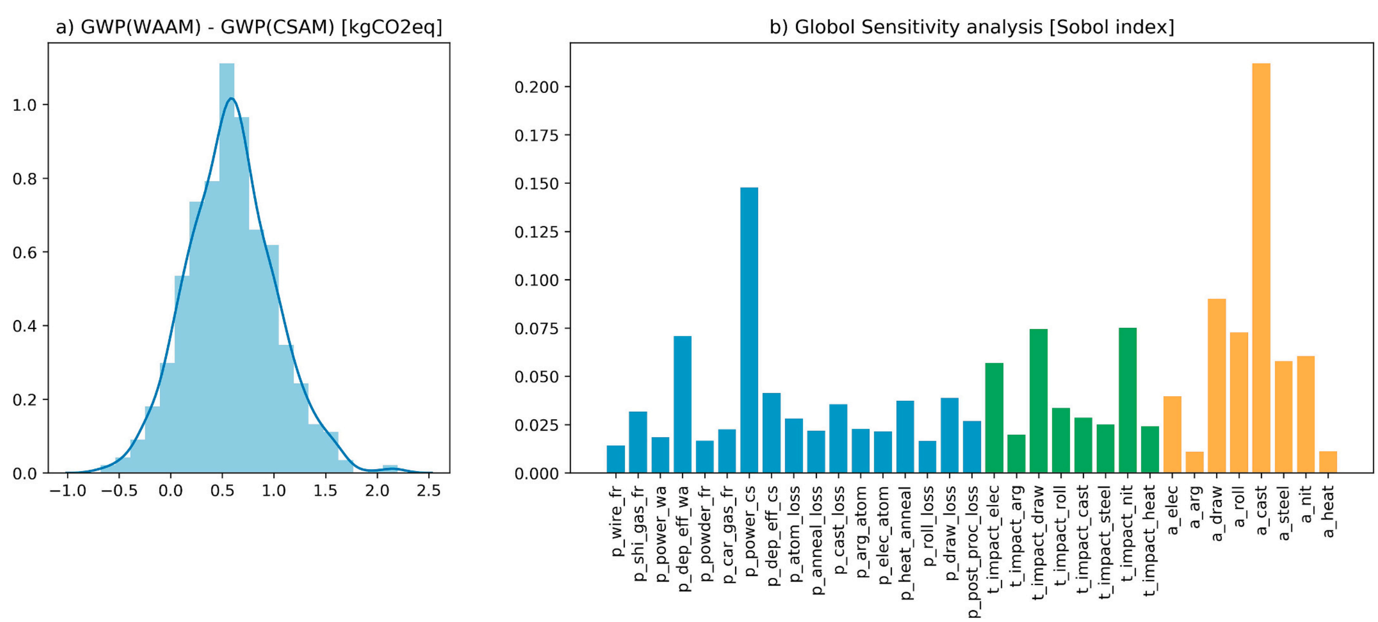

Fig. 5. The results of the third iteration of the a) Monte Carlo analysis and b) Global Sensitivity Analysis. Blue bars are for parameters, green bars for technology (background processes) and orange bars are for applicability.

The Sobol' indices for some background technology flows and applicability uncertainties (green and orange bars) were still as twice higher than those of the parameters, but reducing their uncertainty was considered demanding in time and resources for a further iteration. For example, the Sobol' index of the ecoinvent process of electricity in Quebec is 0.08, where the uncertainty comes from the direct emissions of CO_2 and N_2O (Fig. S4 in Supplementary material 1). Refining this data was beyond the control of Polycontrols, as it would have required a collaboration with the electricity supplier. Therefore, despite not reaching the 95 % convergence criterion, the iterative process was ended and LCA results adopted to support internal decision making after the fourth and final iteration. The final deterministic results and the contribution analysis are available in Supplementary material 1, Fig. S6.

4. Discussion

GSA is mainly used in LCA to assess how robust and realistic the results are (Blanco et al., 2020), determine the main uncertainty drivers on the results (Kim et al., 2022), and empower reliable decision-making in LCA (Baaqel et al., 2023). We leverage the strengths of these applications to use GSA as a data collection guidance and reduce the effort needed to perform an LCA. We illustrated how to apply the framework to guide the data collection in a comparative LCA and showed how the results could change by targeting parameters with high variability. At the end of each iteration, comparing the results to the convergence criteria allows to test the robustness and reliability of the results in respect to requirements defined in the scoping phase of the study. Identifying the parameters contributing the highest to the variability of the results and prioritizing additional data collection around them ensures a systematic way to reduce uncertainty in the results. The case study validates how the framework achieves the targeted objective, and highlights some aspects (e.g., uncertainty range definition and convergence criteria) that need to be refined to improve the reliability of it. For simplicity, only GWP100 impacts were assessed, and a cradle-to-gate system boundary was chosen. Adding more impact categories and including the use and end of life phases is possible under the framework, requiring more knowledge on the application of the product under study. Below we discuss the main learnings and recommendations to address those aspects.

4.1. *Learning 1: the initial screening data might not be accurate, or its uncertainty range might be too narrow*

The framework builds on the concept that the uncertainty range of the initial screening data would be wide enough and encompasses the real data (i.e., the high-quality primary data). As a common understanding, our hypothesis was that by improving the data quality in the additional data collection step, we narrow the range of the uncertainty and converge to the real data. However, this might not be the case, as results are highly influenced by the initial assumptions on the uncertainty ranges (Lacirignola et al., 2017). The uncertainty range of the screening data might be outside the range of the real (high-quality) data, and unless this variability is caught with the global sensitivity analysis, and thus improved, the results might be incorrect. This was the case of powder feed rate in our case study, and this lead to the change of the results (CSAM became worse than WAAM) after the first iteration. If the powder feed rate had not displayed such a high Sobol' Index, the result would have been misleading. Another instance which might lead to misleading results is if the uncertainty range is indeed close to the range of the real (high quality) value, but its uncertainty range is narrow. This could lead to that parameter being missed in the GSA and might lead us to stop the iterations earlier than expected while the value still needs improvement. Thus, defining the uncertainty range should be done with caution, and more rules and guidelines are needed to avoid prematurely ending the iterations. As a general rule, we recommend having the uncertainty range as wide as possible when few data are available, even if it means more iterations are needed. Fig. 7 illustrates such situations where defining the screening data might lead to misleading results. The blue distribution represents the real data (that could also be a deterministic value). The green distribution is what we expected the screening data to look like when the framework was designed, where it is wide enough and incorporates the real data. The orange distributions are likely situations one might end up defining the distribution of the screening data and lead to misleading results.

4.2. *Learning 2: probability that the impact of A is larger than that of B in a Monte Carlo analysis as a convergence criterion needs to be complemented with a GSA*

Another vital step in the framework is defining the iteration

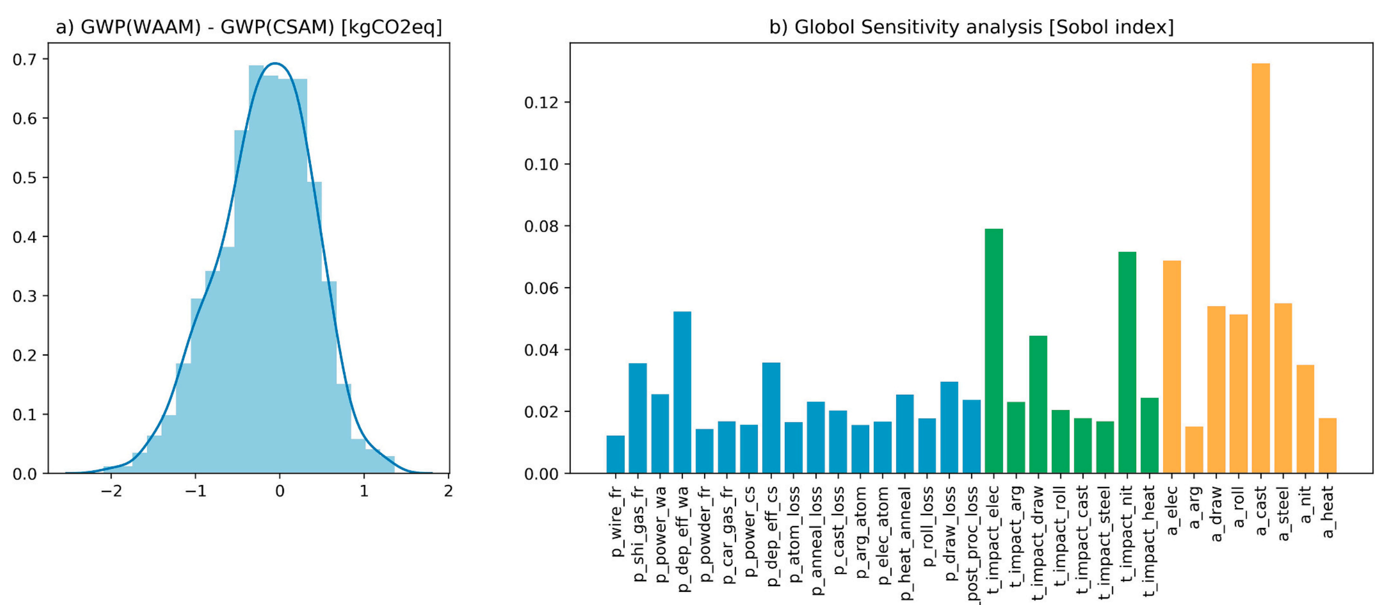

Fig. 6. The results of the fourth iteration of the a) Monte Carlo analysis and b) Global Sensitivity Analysis. Blue bars are for parameters, green bars for technology (background processes) and orange bars are for applicability.

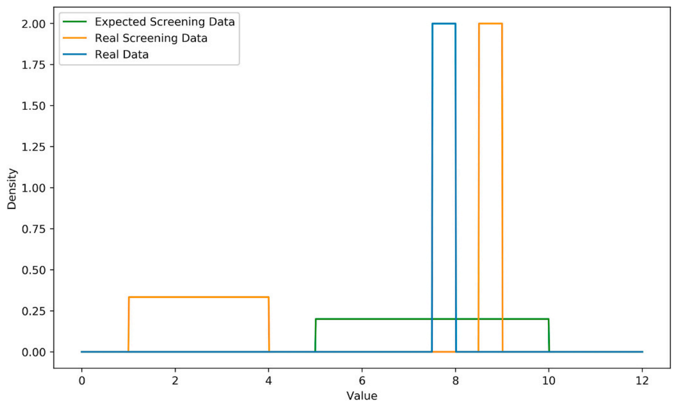

Fig. 7. Hypothetical illustration of uniform probability distribution functions for the expected screening data, real screening data and real data.

convergence criteria. Initially, the criterion was defined as the probability that one product has a higher impact than the other through a Monte Carlo simulation (Fig. 8, left). As demonstrated in the case study, misleading conclusions were drawn at the end of the second iteration despite achieving a probability of 98 %, and only corrected after looking at the GSA results. This is the case when one of the parameters contributed highly to the uncertainty (as demonstrated by the GSA), but its real value was outside the uncertainty range initially defined in the screening data collection. Alternatively, one could define the convergence criterion as a maximum level of Sobol' index that all parameters should be below (e.g., 0.1 in Fig. 8). It is not clear how this threshold should be chosen in the context of an LCA, but in other applications for example, parameters with a Sobol' index >0.1 are considered highly sensitive (Wan et al., 2015). This could also include only foreground data if this is what practitioners have control on or extend to include the background data. We recommend defining such a criterion to complement the likelihood one rather than replace it, as each gives us different indications. Another criterion that could be explicitly defined is the time or cost needed to obtain high quality data (e.g., value of information used by Marchese et al. (2018)) for each parameter (the x ticks in Fig. 8), and how do they compare to the remaining time or budget allocated to the study (the dashed line in Fig. 8).

4.3. Learning 3: using uncertainty analysis might not necessarily reduce time

Hypothetically, acquiring high quality data for fewer parameters would reduce the time to perform the study, but that is not necessarily true. As demonstrated by the case study, high quality data are collected iteratively in a serial effort (i.e., one data point collected after the other) following our approach, while in a traditional LCA data is collected in parallel. Therefore, depending on the number of iterations, the overall time might be longer (Fig. 9). The billable time (e.g., wages for engineers providing the data), on the other hand, is likely to be reduced. That is

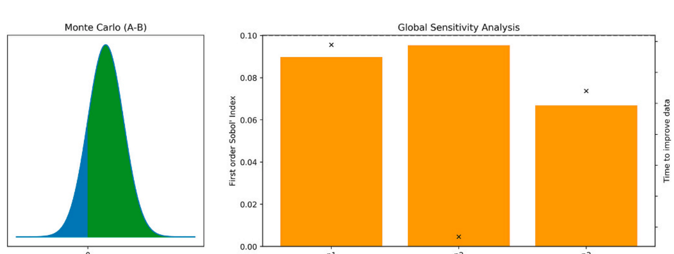

Fig. 8. Hypothetical illustration of various convergence criteria. To the left is Monte Carlo analysis and to the right is Global Sensitivity Analysis complemented with time requirement.

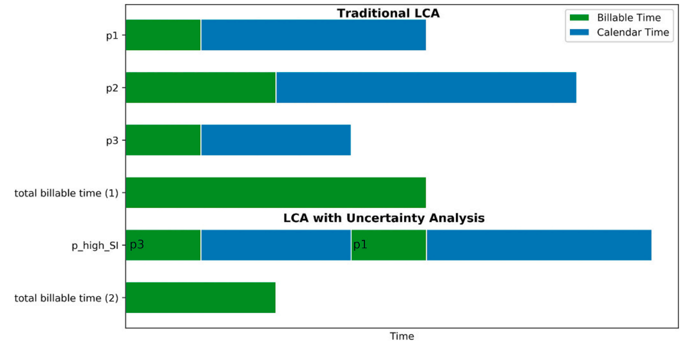

Fig. 9. Hypothetical illustration of the time (billable and calendar) taken to perform a traditional LCA compared with an LCA using uncertainty analysis to guide data collection. p stands for parameter and p_high_SI stands for the parameter with the highest Sobol' Index.

because most of the time needed for the data collection, as we experienced in the case study, was calendar time. We define calendar time as time that does not incur any cost, which is mainly idle waiting time (e.g., waiting for an answer from an expert, waiting to reserve a lab for an experiment, etc. …). For some studies, where the deadline is the constraint (rather than the budget), calendar time would be important. Note that additional time for the screening data collection and the Monte Carlo/GSA calculations could add more time to our proposed framework, but is considered negligible compared to the time to collect high quality primary data.

5. Conclusion

In this study we proposed a framework to prioritize data collection in comparative LCAs using global sensitivity analysis (GSA). While GSA was proposed for other applications of LCA, it is perceived as demanding for practitioners, and with a structured framework, we hope this would increase its adoption. GSA ranks the parameters influencing LCA inventory data based on their contribution to the variability of the output, enabling practitioners to focus data collection efforts on high contributing ones while minimizing the time needed to reach conclusive results. A case study comparing two additive manufacturing technologies demonstrated its applicability. Although the case study was on additive manufacturing technologies, the framework is applicable to other industries, particularly when comparing two alternatives. The framework, however, needs to be handled with caution, as the results are highly influenced by the initial definition of the uncertainty distributions of the data collected through a screening approach. More specifically we brought out that extreme care is needed when defining and using probabilistic values instead of deterministic ones, and we call practitioners for more uncertainty data inclusion when sharing inventory data. In addition, choosing the convergence criteria for conclusive results based on uncertainty propagation techniques such as Monte Carlo alone is not enough. We recommend complementing it with the definition of a maximum Sobol' index criterion not to be exceeded. Despite that, the framework gives higher clarity of communication between practitioners and decision-makers, who need to understand the level of confidence of the results and choose the risk levels they are satisfied with given the resource constraints.

CRediT authorship contribution statement

Mohamad Kaddoura: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Guillaume Majeau-Bettez:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Ben Amor:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Manuele Margni:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2025.179269.

Data availability

The data is available in the Supporting Information.

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