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UNCERTAINTY SOURCES IN LCA, CALCULATION METHODS AND IMPACTS ON INTERPRETATION

SUMMARY

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SCORE LCA is an association that has been created to financially support collaborative research on LCA and related topics. It aims to promote and organize cooperation between companies, institutional and scientists in order to support the evolution of LCA methods and its practical implementation at European and international level.

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Life Cycle Assessment (LCA) scholars are interested in the reliability of the LCA outcomes by developing quality indicators, sensitivity and uncertainty analyses approaches since the beginning of the 90s. Nowadays, research focuses on the application of advanced techniques (e.g. Bayesian inference, fuzzy logic, Sobol indices), which are however rarely applied by practitioners due to lack of knowledge, time, data, user-friendly tools or relevance. Therefore, the LIST team explored this research field within the framework of the study 2014-03 for SCORELCA association in order to give an overview of the uncertainties sources, their characterization and analysis in LCA, as well as recommendations for the application of available approaches depending on the context and objectives of the LCA study. For each topic mentioned in this report (interest and context, uncertainty characterization, uncertainty and sensitivity analysis approaches, and results communication), we will briefly present the state of the art (deliverable D1.2), results of the online survey about current practices and recommendations from the guidelines (deliverable D3).

1. Interest and application context of the analyses

State of the art

Uncertainty analysis evaluates the result uncertainty due to the uncertainties of model inputs. Therefore, this analysis is based on uncertainty propagation methods. The result is the quantification of the uncertainties of the model output. Sensitivity analysis evaluates the effect and influence of inputs uncertainties on the results in order to identify the main parameters affecting the model. While the local approach focuses on the model answer from small variations around the inputs values, the global analysis explores the entire space of the parameters in order to determine the contribution to the parameter uncertainty on result uncertainty. It is then possible to decrease the results variation by trying to improve the quality of parameters whose contribution is the highest in order to refine the LCA model. Quality analysis allows aggregating quality criteria (representativeness, completion, etc.) to define a probability distribution of parameters. It is therefore a support for uncertainty and sensitivity analysis and will be detailed here in the section of uncertainty characterization. The reviewed LCA studies performing one of these types of analysis deal with all types of sectors (agriculture, energy, waste, construction, etc.).

Results from online survey

Practitioners who answered the online survey often apply sensitivity analysis while uncertainty analysis is used less. The main barriers for the application of these studies is the lack of data and time, as well as the lack of utility/added value for sensitivity and lack of reliability of methods/tools for uncertainty. It has to be noted that the other proposed factors from the questionnaire (lack of relevance, tools or knowledge) were also mentioned. This shows that besides the constraints linked to the study data and time), an effort should be made to demonstrate the interest of these analyses and to implement them in reliable tools. The main reasons to perform these analyses are the results validation, better understanding and refinement of the LCA model. In majority, they are applied in the framework of a comparative study. Applications for eco-design, environmental report and policy evaluation are also often subject to sensitivity or uncertainty analysis. The survey highlighted the lack of correlation between the sector of the LCA study and the analyses application.

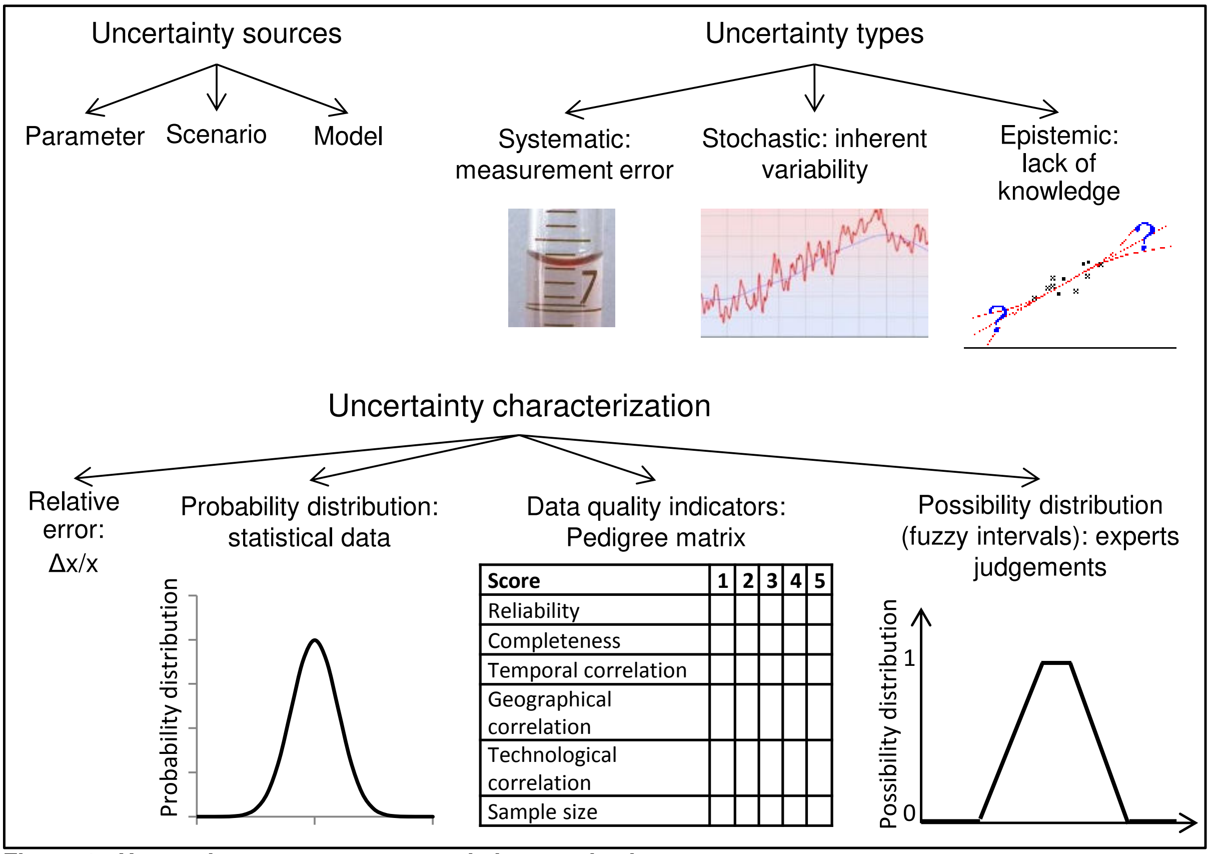
Recommendations

First, we should notice that sensitivity and uncertainty analyses are mandatory for a comparative study communicated to the public (ISO 14040-14044, 2006). Sensitivity analysis can also be required for an environmental declaration of a product. Besides these obligations, we highly recommend to evaluate the sensitivity and uncertainty of a LCA study when it is used for decision support (e.g. eco-design, policy evaluation, comparative study, consequential approach). Indeed, the practitioner can then estimate the validity degree of the study conclusions and move more easily towards a choice scientifically proven. It is also very important to perform sensitivity and uncertainty analyses for all types of communication to the public in order to avoid a biased interpretation and potential greenwashing because LCA assumptions can easily be diverted to move the results towards the objective of an LCA commissioner. It is therefore essential to test their influence to ensure the conclusions validity. We also see a high utility in the case of model development (for inventory or impact). Sensitivity and uncertainty analyses prove the model reliability and can also allow refining it, which will facilitate its use. Finally, even if the LCA study does not correspond to one of the cases previously cited, we recommend to perform sensitivity and uncertainty analyses (if enough time and budget). Effectively, since the LCA results are not physically measurable, they are not verifiable. The quality of an LCA study is therefore directly linked to the robustness of the data and models used. It is therefore important to identify the uncertainty sources to improve the model quality and understand their effects on the results in order to validate them.

2. Uncertainty characterization

State of the art

It is possible to classify uncertainty depending on its systematic (imprecision linked to the experimenter and/or measurement instrument), stochastic (data and system variability, phenomenon hazard), and epistemic (lack of knowledge on data, models or rules describing the system) nature. In LCA, uncertainty can come from the definition of parameters (measurements of consumptions, pollutants concentrations, etc.), of scenarios (e.g. system boundaries, allocation rules) or of models (e.g. process simulation, cause-to-effect chain). Characterization can be done through relative error (difference between measured value and real value). Statistical data can define probability distribution of parameters (e.g. uniform, normal or log-normal) with indicators such as mean, variance or confidence interval. It is also possible to use data quality indicators (reliability, completeness, temporal correlation, geographical correlation, technological correlation and sample size) via the Pedigree matrix, which are converted into probability distributions. The approach used by the ecoinvent database (Frischknecht et al., 2007) is considered as the consensus. Finally, possibility distributions (often triangular or trapezoidal) can be determined from fuzzy intervals (possible values with a given membership degree). The interval for a membership degree of 1, called core, reflects the preference values and all the elements with a non-zero membership degree represent the support and therefore all the possible values. The classification of sources, types and characterization of uncertainties is presented in Figure 1.



Score	1	2	3	4	5
Reliability					
Completeness					
Temporal correlation					
Geographical correlation					
Technological correlation					
Sample size					

Figure 1 : Uncertainty sources, types and characterization

Results from online survey

The survey showed that the LCA practitioners most often use probability distributions and data quality indicators, and to a lesser extent the variance. No respondent chose the fuzzy intervals (possibility distributions). They rely on measurements, experts' judgements or literature data. A few participants raised the issue that measurements are rarely available.

Recommendations

The recommendations only concern quantifiable parameters since uncertainties linked to the model or scenarios definition (e.g. choice of characterization method, of the cut-off or allocation rule) can only be dealt with scenarios analysis (implemented in all LCA software tools).This latter should involve stakeholders in order to decrease the uncertainties (Zamagni et al., 2009).
For quantifiable uncertainties, the most precise way to characterize them is from statistical data to define the probability distribution of the parameter (e.g. monthly data, continuous measurements of chimney gazes, etc.). Measurements of statics database should then be favoured, with a sample size large enough to deduct the type of distribution and its characteristics. The type of distribution can be determined visually (e.g. with CMLCA) or based on statistical tests. The most direct way is a visual determination.
If the sample size is very small or if no statistical data is available, several choices can be made by the practitioner:
- First, an expert of the data supplier can estimate the parameter variance (e.g. ±10%). In this case, no assumption on the distribution is made and an analytical approach will be used for sensitivity and uncertainty analysis.
- In another case, the practitioner can perform a quality analysis via the Pedigree matrix to estimate the standard deviation (automatic calculation in OpenLCA and CMLCA). This method is however for now only applicable for log-normal distribution, considers generic

factors that can not be adapted to the studied system and can overestimate the error when the quality criterion is unknown. Some improvement work is currently in progress (Ciroth et al., 2013; Muller et al., 2014) and should be continued in order to obtain more representative uncertainties.

- Finally, the definition of possibility distributions can also be a solution to face the lack of data. In this case, the practitioner relies on expert judgements to define the support and core intervals. However, the uncertainties propagation based on fuzzy logic lack of application and practical tools. It also suffers from low reliability and high subjectivity. We therefore think that this method should be still developed before being used by practitioners (especially industrial ones).

3. Approaches

State of the art

Statistical sampling approaches perform several results simulations based on the sampled values from the inputs probability distributions. They give the distribution of results but require tedious data collection and intensive calculations. The Monte Carlo method (random sampling) remains the most used because it is implemented in all common LCA software.

However, approaches such as Latin Hypercube (stratified sampling) or Bayesian Monte Carlo (update of distributions with newly observed data) are more refined but require the use of non-LCA tools.

Analyses based on fuzzy logic (fuzzy arithmetic from the LCA matrix or fuzzy inference system from qualitative rules and judgements) allow treating possibility distribution, which facilitates the data collection process. They remain used in a marginal and theoretical manner, and they are not present in any LCA software.

Hybrid approach, being used in only one LCA publication, allows sampling on both probability and possibility distributions to define distributions family of the results.

Analytical analysis via Taylor series expansion applied to LCA matrix, implemented in CMLCA, allows a non-intensive calculation of the results variance and requires only the data variance as inputs but the results are less robust (mathematical approximation only valid for small variations). Correlation between variables was taken into account only with the Monte Carlo approach and its feasibility should still be proven for the other methods.

An overview of the approaches is shown in Figure 2.

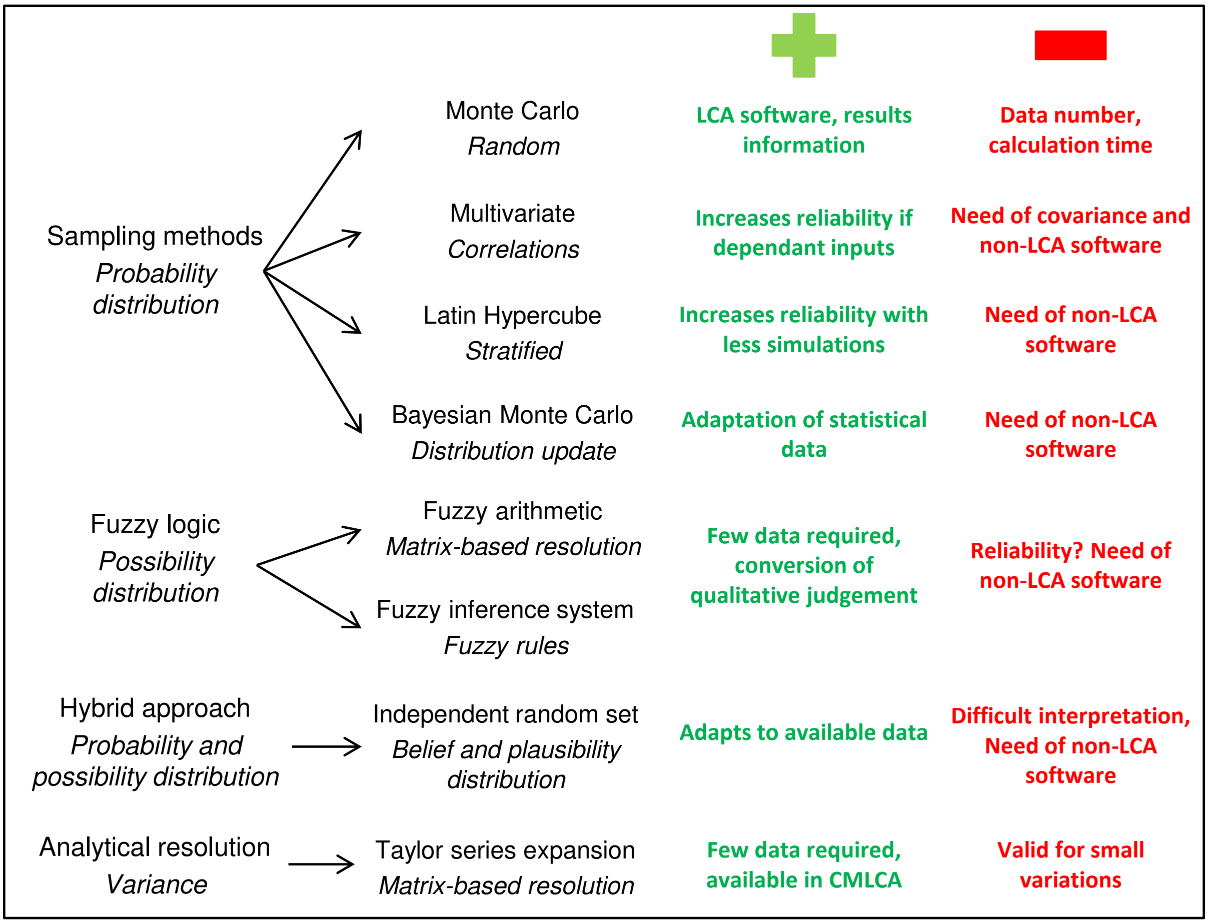


Figure 2 : Advantages and drawbacks of uncertainty analysis approaches from literature review

Local sensitivity analysis proves to be very practical (ease of use, only minimum data required) to test methodological choices or effects of parameter variations. These analyses of scenarios or variations one-at-a-time are generally implemented in all LCA software.
A more “scientific” approach based on the matrix derivatives is available in CMCLA.
Global sensitivity analyses give more information on the model sensitivity. The method of elementary effects quantifies the importance and non-linearity effects of input parameters, based on successive variations of these latter on their definition domain.
The approaches of variance decomposition evaluate the contribution to the inputs variation to the results variation. In the case of Fourier or Sobol methods, they can also estimate the interaction effect thanks to the difference between the total order index (sum of all sensitivity indexes, including interaction effects) and the first order index (contribution to the variance of each parameter individually). However, these latter require probability distribution of input data, more calculations and the use of non-LCA tools, which has restricted their application until now.
Advantages and drawbacks of the methods are summarized in Figure 3.

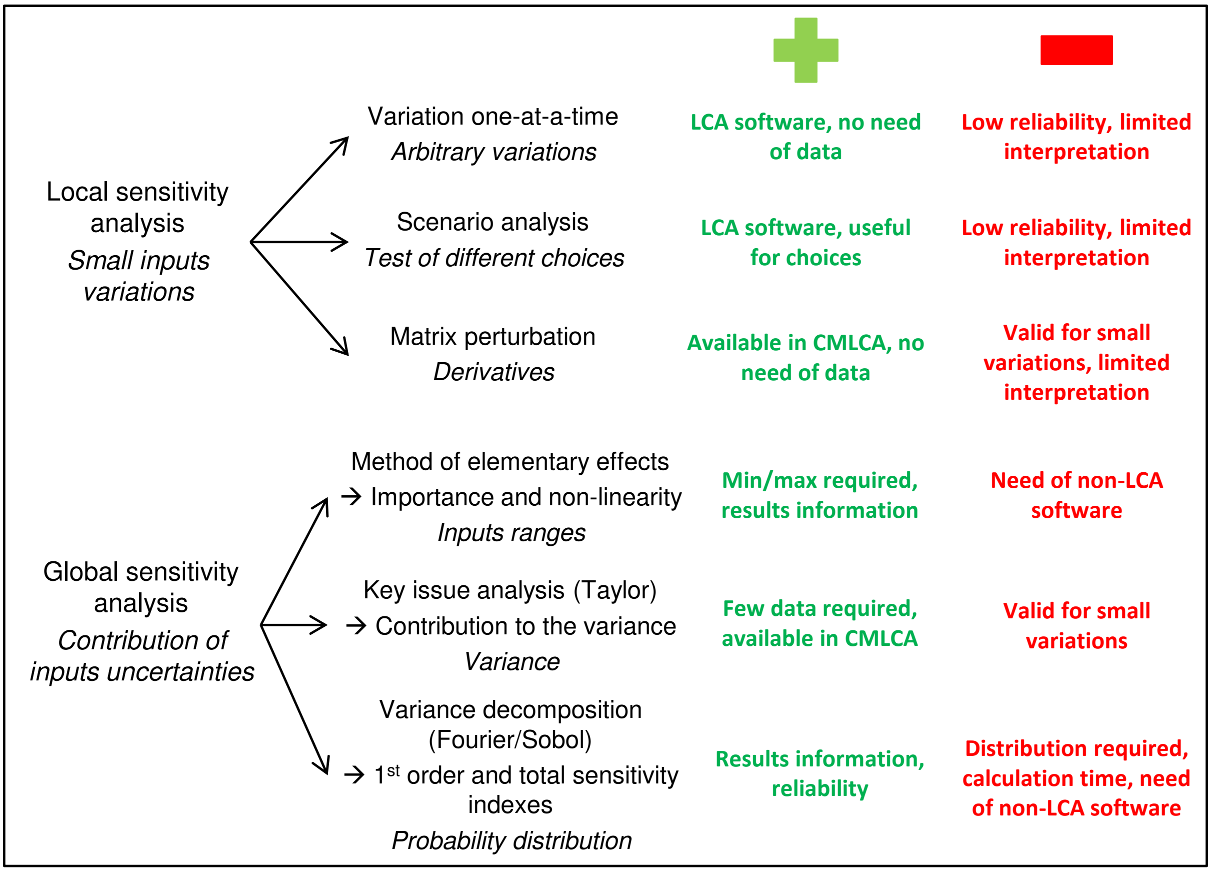


Figure 3: Advantages and drawbacks of sensitivity analysis approaches from literature review

Results from online survey

Most of the sensitivity analyses rely on the techniques of variations of parameters one-at-a-time and scenarios analysis. The other methods have been marginally used, in general since 2010 and with more experience.

For uncertainty analysis, the Monte Carlo approach is in majority used (often since the first year of practice), and the derived methods (Latin Hypercube, Quasi Monte Carlo, Bayesian Monte Carlo) are applied to a lesser extent and after a few years of experience. The other approaches are rarely applied.

Concerning the software, SimaPro is the most used, Gabie, MATLAB/Scilab, R and OpenLCA come after. Persons choosing other tools perform most of the time more complex analyses than the one proposed by common LCA software (variations one-at-a-time, scenario analysis and Monte Carlo sampling).

Recommendations

Since the uncertainty characterization for model parameters can turn out to be long and complicated, we propose to set a maximum number of studied variables before starting the analyses. Here, we choose a limit of 20, which can be modified depending on the available time, budget and data. If the number of quantitative uncertain parameters is higher, it is then recommended to prioritize the ones with high contribution to results and uncertainty level (data quality, variability, etc.), as it is done in the ILCD handbook (European Commission, 2010). Concerning the choice of approaches, we distinguished the recommendations depending on the type of tools used because the common LCA software (SimaPro, GaBi, Umberto, OpenLCA and CMLCA) do not include advanced analyses (e.g. Latin Hypercube sampling, global sensitivity analysis) which can be performed by more complex tools (e.g. Brightway2, MATLAB, Crystal Ball).

Concerning the common LCA tools, the consideration of correlations is not possible. If there are some known relationships between variables, currently the only solution is to express the uncertainty of one parameter and to calculate the value of the dependent ones based on this latter. If probability distributions can be determined (either from statistical data or from Pedigree matrix), a Monte Carlo analysis can be performed to visualize the result distribution and therefore know its characteristics (mean, confidence interval, etc.). If background processes are included in the system boundaries, we recommend using the ecoinvent database with unit processes in order to consider background uncertainties. The number of simulations should be high enough to obtain a representative distribution (at least 1000 simulations or more if possible).

SimaPro, OpenLCA and CMCLA software should be chosen in priority because they include this type of sampling, as well as the use of background uncertainties and various distribution types.

Concerning the sensitivity analysis, the only functionality offered by the tools (apart from CMLCA) is the variation of parameters one-at-a-time. However, instead of using arbitrary percentage as it is often done by the practitioners, it is more relevant to use the real variation domains to identify realistic effects on the results. When uncertainty is characterized by the variance, the practitioner is obliged to use CMLCA software. Uncertainty analysis via Taylor approximation can calculate the results variance and sensitivity analysis based on key issue analysis identifies the contribution of input variations on results variation. As highlighted by Heijungs & Lenzen (2014), this method based on model linearization is only valid if the error terms are not so big. The application of the method to variable with large uncertainties could then overestimate the results variance.

In the case of advanced tools, the changes compared to the use of common LCA software concern the treatment of probability distributions. First, if background uncertainties are taken into account (ecoinvent database with unit processes), it means that the number of uncertain variables is from several tens of thousands order. The advanced approaches of global sensitivity analysis cannot deal with so much data. It is recommended to perform a priori a local analysis with matrix perturbation (available in CMLCA software) and the method of elementary effects (e.g. with Pyhton script, MATLAB, etc.) to decrease the number of studied parameters, as done in Wei et al. (2015) and Mutel et al. (2013). Then, the correlations between the remaining parameters need to be investigated. The correlation coefficient (number between -1 and 1, null for independent variables) can be calculated in a theoretical manner but this remains difficult in practice (lack of data). We can then move towards an empiric determination, as the one proposed by Wei et al. (2015), even if this can seem arbitrary and subjective. If the model does not include correlation, we can perform a global sensitivity analysis via variance decomposition (Fourier or Sobol) to determine the first order and total sensitivity indexes.

Uncertainty analysis can finally be performed with sampling method to determine results distribution. We consider that the Latin Hypercube approach is the most efficient because it limits the number of simulations thanks to a stratified sampling. In the presence of correlations, the analysis methods are the same but with some modifications to consider correlations. For the sensitivity, de Koning et al. (2010) and Wei et al. (2015) grouped correlated variables to calculate the sensitivity indexes for clusters. Finally, a multivariate sampling should be applied for uncertainty analysis, as in Bojaca & Schrevens (2010). Probability distributions are modified to consider the covariance matrix of parameters.

For the future, several research pathways could be investigated. For example, the implementation of fuzzy logic, which represents an alternative in the case of lack of data, needs further research efforts to validate the propagation method for possibility distribution but also practical tools that will allow to apply it for non-simplified LCA studies. An important future advancement concerns the improvement of uncertainties characterization and analyses methods in LCA software. Indeed, for now, some tools can deal with background inventory uncertainties but they should also include uncertainties linked to characterization factors from impact assessment methods. Moreover, we noticed that the available uncertainty and sensitivity analyses lack of reliability (either for the consideration of correlation or for sensitivity analysis based on input uncertainties) and require long calculation time. Software developers are currently working on these improvements (e.g. it is possible that GreenDelta GmbH, developer of OpenLCA, is elaborating a tool for global sensitivity analysis).

4. Results interpretation and communication

State of the art

Sensitivity analysis results allow classifying input parameters depending on the effect of their uncertainty on result variations and therefore refine the LCA model.
Conclusions from uncertainty analysis determine the results variation, which is particularly useful for a comparison of alternatives.
When we deal with probability distributions, the impacts difference between two systems is considered significant if the 95% standard deviation does not include the zero value. It is also possible to perform statistical tests to evaluate if the difference is statistically significant, such as the t-test implemented in CMLCA software. In the case of possibility distribution, it is possible to transform them in probability distributions (André & Lopes, 2012) and therefore follow the previously cited rules. Otherwise, Weckenmann & Schwan (2001) define that a product A is better than a product B if the uncertainty domains do not overlap (or only a little bit) or if they overlap but they have the same amplitude.
Finally, concerning the use of variance of the compared alternatives, Hong et al. (2010) determine the probability that a scenario A is better than a scenario B if the variance of the ratio A/B is lower than 1. This latter is calculated based on the parameter variances of the two scenarios.

Results from online survey

The practitioners in majority answered that they use the results of uncertainty and sensitivity results to put the conclusions in perspective but a high number of respondents also use them to refine the LCA model in an iterative process.

Recommendations

In the case of a comparative study, uncertainty analysis allows supporting the decision because it determines if the observed difference is significant or if it is only due to LCA model uncertainties. When no preferences can be distinguished because of results uncertainties, the main influencing factors to results variability should be understood and a sensitivity analysis should be carried out. The key parameters identified can then be investigated in order to try to refine the model (e.g. obtain additional data, ask for experts to judge implemented uncertainties) and obtain less uncertain results.
For a non-comparative study, the uncertainty and sensitivity analyses allow informing about the reliability of results and models. Effectively, if the results variability is high (e.g. higher than one order of magnitude), the practitioner should then understand its origin and try to decrease uncertainties. Without this, he/she does not have any idea of the results precision, uncertainty effects, interaction or non-linearity effects of the LCA model.
When the LCA study is intended for industrials or stakeholders (within the framework of B2B communication, policy strategic support or product ecodesign), the results should remain readable and understandable. It is then possible to display the standard deviation, the variance or confidence intervals which are easily understandable indicators. The conclusions from sensitivity analysis can be formulated in a qualitative manner to highlight the main uncertainty factors (e.g. by adding in parallel of impacts contributions, the effects of input parameters uncertainty).

If the results are communicated to LCA experts, in the frame of model development or other research work, the detail level can be high. Indeed, the methodology and results transparency is even more important if other users want to reuse the study conclusions. A documentation effort should be done, as in Cucurachi (2014) for the characterization model of noise impacts, Mutel et al. (2013) for characterization factor of land occupation and Sonnemann et al. (2003) for inventory of electricity production.
To conclude, it is obvious that the practitioner should adapt to the target audience of the LCA study but we should however move towards a more transparent communication where results from uncertainty and sensitivity analyses are mentioned, even if it is in a qualitative manner.

5. Conclusions

In conclusion, the study allows clarifying the concepts around quality, sensitivity and uncertainty analysis. From the state of the art and survey results, we could draw practical recommendations for the uncertainty characterization, for the implementation of these approaches in LCA, and for the results interpretation and communication depending on the context and objectives of the study. Some research efforts should be continued to facilitate the application and improve the reliability of the uncertainty and sensitivity analyses, especially regarding the implementation of data and functionalities in common LCA software tools.