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A comparison of uncertainty propagation methods in an LCA study

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1. Introduction

Uncertainties underlying life cycle assessment (LCA) results are often raised as a major obstacle to a broader use of LCA in decision making. Uncertainties arise at different stages of the life-cycle analysis and can be usually ascribed to three types: model, scenario and parameter uncertainties [1]. Thus uncertainty analysis has become a major topic of methodological development over the last years [2].

In the absence of any recommended method, several approaches are being undertaken by LCA practitioners to evaluate sensitivities and uncertainties of their results. These range from simple scenario analysis, whereby different alternatives are tested, to more advanced uncertainty propagation methods. Uncertainty propagation typically consists in first defining the uncertainties affecting model input data to secondly propagate them through the model and thus evaluate the uncertainty of the LCA results. Several methodologies can be used for defining and propagating uncertainties in LCA studies, according to the nature of available information. Two such methodologies are provided by probability and possibility theories. Probability theory is the most commonly used [3] and consists in defining uncertainties as single probability distributions and then propagating them through stochastic modelling (e.g. by Monte Carlo or Latin hypercube simulations) as shown e.g. by [4] or analytically (e.g. in [5]). For cases where available information does not justify the use of single probability distributions for representing uncertainty, possibility theory provides an alternative method which consist in defining uncertainties as nested intervals (or fuzzy sets e.g. [6]).

The objective of this paper is to illustrate the fundamental differences between these approaches using on the one hand classical stochastic modelling, fuzzy calculus, and finally a hybrid method which combines both approaches. The advantage of the latter is that the manner in which model input uncertainty is represented, can be more consistent with what is actually known regarding the input (available information).

2. Materials and methods

2.1. Presentation of the case study

The case study investigates the benefits of source-separating the organic fraction of household waste to send it to anaerobic digestion instead of incinerating it together with residual waste, in Danish conditions. The functional unit is the collection and treatment of 1 tonne of biowaste from Danish households in 2011. For the purpose of clarity, only the global warming potential impact is considered in this case study. Moreover, due to uncertainties common to the two scenarios, only the differences between the results of the two scenarios are presented.

Prior to the uncertainty propagation, a sensitivity analysis enables to reduce the number of parameters to 26. For each of these parameters, data was gathered through a litterature review among different LCA databases and articles. This served to define the uncertainties underlying each parameter, using either a single probability distribution representation, or else a fuzzy-set representation.

2.2. Implementation of the stochastic modelling

Probability distributions were selected for each parameter based on the data available. Most of the distributions were chosen as log-normal as this distribution only allows positive values. Uncertainties were then propagated using a Monte Carlo analysis of 10 000 runs.

2.3. Implementation of the fuzzy calculation

For each parameter fuzzy sets were defined based on the same data. The fuzzy sets were defined using two nested intervals: an interval outside which values were considered not possible (the support of the fuzzy set)

and an interval of values considered most likely (the core of the fuzzy set). The uncertainty propagation was performed using the method of α-cuts presented by [7].

2.4. Implementation of the hybrid method

In this third method, some parameters were represented by single probability distributions (because they could be justified by available data), while others were represented by fuzzy sets (because available data was incomplete and/or imprecise). The joint propagation of these different modes of uncertainty representation was performed using the IRS method (independent random set) proposed by [8]. This method performs a random sampling of both probability distributions (leading to point values) and fuzzy sets (leading to intervals). An optimization technique then serves to find the extrema (minimum and maximum) of the model output for these point values and intervals. Multiple iterations, as for the classical Monte Carlo method, provide a model output in the form of a family of probability distributions, the spread of which reflects the incomplete nature of input information.

3. Results and discussion

Comparison between the three propagation methods illustrates the very conservative nature of the purely fuzzy calculation, which encompasses a family of probability distributions, of which the result of the purely stochastic calculation is but one representative among others. Results of the hybrid calculation on the other hand are more precise than the fuzzy calculation (the spread of the probability family is less important) but of course less precise than the purely stochastic result which assumes that single probability distributions are perfectly known for all input parameters.

4. Conclusions

In real-world situations of LCAs, available data relative to model input parameters are typically of different natures: the data may be "rich" (e.g. many measurements) therefore justifying the use of single probability distributions, or it may be "poor" (e.g. expert judgment, literature data, etc.), which is more adequately represented by the nested intervals of fuzzy sets. In such a case, the proposed IRS method can serve to jointly propagate the different types of uncertainties in the LCA. Such an approach is deemed preferable to arbitrarily defining single probability distributions in presence of imprecise/incomplete information, thus conveying an illusion of precision that is not justified by available data.

5. References

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