Treating Input Data Uncertainty in LCA: Monte Carlo and Fuzzy Approaches

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Abstract

This work aims at discussing the differences between Monte Carlo method and Fuzzy data sets approaches when dealing with input data uncertainty in LCA models. Input data variation is treated in most LCA studies considering uncertainties because practitioners do not have the necessary specific data for the case study or even because the available data has a characteristic variation. In this work the probabilistic and the possibilistic approaches are detailed discussed and the probability density function and the membership function curves of the respective results are compared, through the application of both methods in a simple case study. It consists of two materials mainly composed of recycled cotton fibers used as acoustic barriers in automotive vehicles: DL (Dual Layer) and ABA (Absorption, Barrier, Absorption). The Monte Carlo Method was applied through SimaPro®. The lognormal probability density function adapted to the result data showed that DL material is more impacting then the ABA one in the Acidification category, however in the Photochemical Oxidation category, there is an intersection between the curves and in this interval there is a chance of both materials to be the most harmful for the environment. The same results were observed through the membership functions of these impact categories when applying the Fuzzy data sets approach; therefore, probabilistic and possibilistic approaches were validated for the treatment of input data uncertainty in LCA models and they can be useful tools for LCA practitioners.

Keywords: *Life Cycle Assessment, Input data uncertainty, Monte Carlo Method, Fuzzy data sets*

1. Introduction

The Life Cycle Assessment (LCA) methodology provides information for the improvement and the comparison of products' environmental performance. This is a relatively new research field, with its first publications dated from the 80's, therefore there is not a great quantity of guidebooks, standard case studies, unquestionable impact assessment methods or specific databases for all cases. This situation can lead to variations in LCA practitioners conduct and also in their results. So it is important to consider uncertainties in LCA studies, because as in any modeling activity that simplifies the reality, there are sources of uncertainties which directly affect the results. To show the frequency of uncertainty analysis in the LCA research field, Ross et al. (2002) surveyed 30 studies and observed that from these, 47% mentioned uncertainty, 7% performed qualitative analysis and 3% performed quantitative uncertainty analysis.

ISO standard (2006) recommends LCA practitioners to perform quantitative uncertainty analysis in their studies, but is does not tell exactly how and this generates differences among the approaches observed in the literature. For instance, there are differences in the uncertainties classification: while Hiujbregts (1998) classifies the types of uncertainties in LCA as: parameter uncertainty, model uncertainty, uncertainty due to choices, spatial variability, temporal variability and variability between sources and objects, Lloyd (2007) only separates uncertainty types in parameter, scenario and model.

The uncertainties propagation method should be chosen according to the type of uncertainty studied in the case. Most LCA practitioners deal with uncertainty in the input data, because they rarely have all the necessary specific data for the studied case. To treat this kind of uncertainty they generally chose stochastic modeling (generally Monte Carlo Method) (Sonnemann et al., 2000), fuzzy data sets (Weckenmann et al., 2001), or interval calculations (Chevalier et al., 1996).

In this work, the mathematical manipulations from Monte Carlo method and Fuzzy data sets used to deal with input data uncertainty in LCA were detailed discussed. First, the MC approach is discussed based on SimaPro® statistical tool. Then the Fuzzy data sets approach is shown. A simple case is used as an example for both methods and the probability distribution curve of the MC results are compared with the membership function curve of the Fuzzy results. The aim of the study is to note the differences between MC and Fuzzy approaches in LCA models and to observe if they generate equivalent results.

2. Method

Figure 1 shows a scheme of a LCA deterministic model. The input data that constitutes a material or a product are inserted. These data can be raw material, energy, transport, production process, end-of-life treatment and so on and they are composed of Elementary Fluids (EF's) - chemical substances, water consumption, land occupation, etc. When summing respectively the different EF's of each data, it is possible to obtain the inventory table of the complete product. This table is multiplied by the impact category table from the impact assessment method chosen and all EF's turn into the same unit - the unit related to that impact category - and they can be summed. This sum is the result value of that impact category.

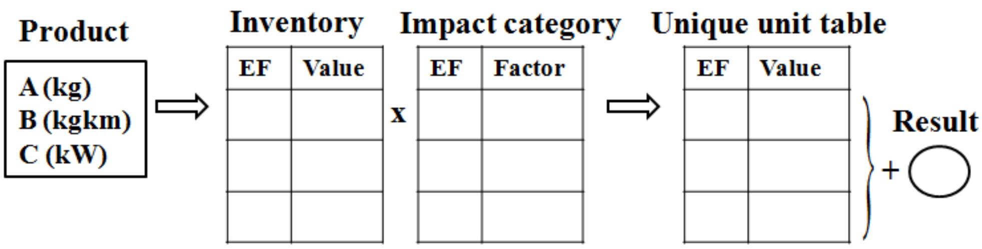


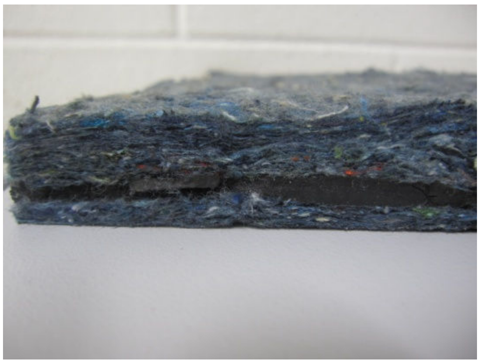
Fig. 1 Deterministic schema of the calculations in an LCA deterministic model

In an LCA case study in which the input data are admitted with a certain variation, the probabilistic and the possibilistic approaches can be made. The main difference between these approaches is that the probabilistic one requires more information about the random variable in order to define its mean, standard deviation, and Probability Density Function (PDF), while the possibilistic one only demands an interval in which this variable is admitted. One way how to define a PDF in a probabilistic approach is to use the Principle of Maximum Enthropy (Kapur et al, 1992) which based on some characteristics of the random data is able to define the best PDF for it.

The probabilistic method assumes a mean, a standard deviation and an adequate probability density function to this data. Then a certain number of realizations are made until the convergence is achieved and the behavior of the results in function of the input data variation can be explored. The result data distribution can be fitted to a probability density function curve. This procedure defines the Monte Carlo Method. The possibilistic method assumes the random input data as Fuzzy data sets (Hanss, 2005) with a certain membership function and a discretization. The calculations are all made in function of these two characteristics and the results are obtained with a membership function curve. As the results of both approaches are adjusted to curves, with the difference of a scalar value, they can be compared.

3.1 Monte Carlo

The MC method (Haldar et al., 2000) was applied in a simple example of 1kg of two materials used for acoustic isolation in vehicles. The Dual Layer (DL) material is composed of scraps of cotton and polyethylene (PE) and the Absorption/Barrier/Absorption material (ABA) contains these two materials and also cement and calcite. Figures 2 and 3 show a zoom of ABA and DL materials. They are produced by Coplac®, an industry located in Itu, Brazil.



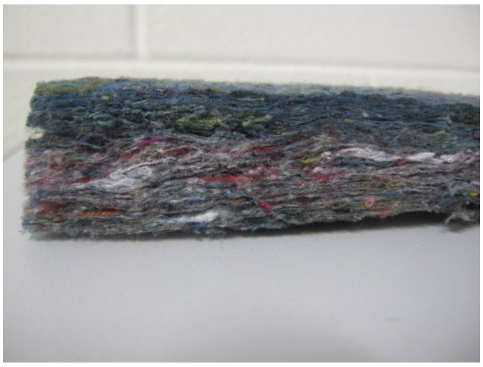


Fig. 2 ABA material lateral zoom **Fig.** 3 DL material lateral zoom

The quantities of raw material were assumed with 10% of variation, but they cannot be mentioned for confidentiality reasons. As SimaPro® software provides uniform, triangular, normal, and lognormal PDF's, the lognormal one was chosen, because it does not assumes negative values. In each simulation, random values for PE, calcite, recycled materials and cement were generated, an inventory is generated, multiplied by the impact categories' tables and the results are obtained with their statistical characteristics: mean, standard deviation, coefficient of variation, median, etc. Ecoinvent® database and CML 2® baseline 2000 impact assessment method were used. A quantity of 1000 realizations that lasts approximately 5 minutes guaranteed the convergence of the results, as observed in Figures 4 and 5. Table 1 shows the means, the standard deviations (std), and the coefficients of variation (COV) of the Photochemical Oxidation (PO) and Acidification (A) impact categories of both products.

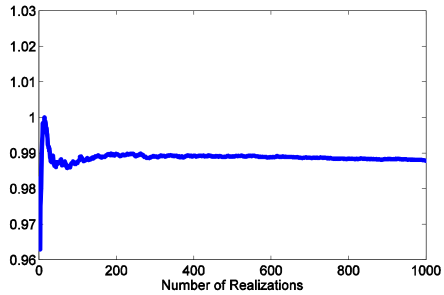


Fig. 4 ABA material model convergence of PO impact category

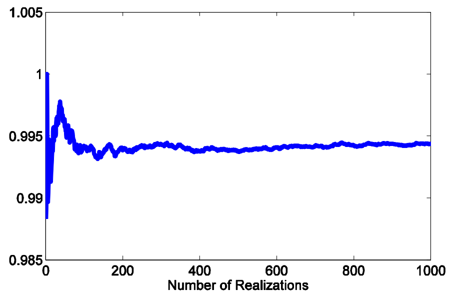
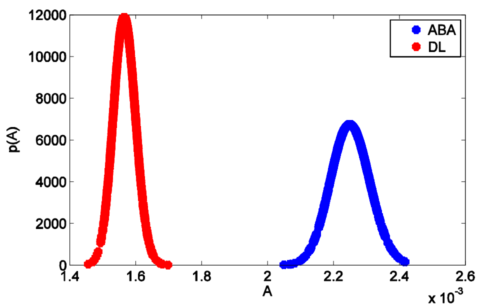


Fig. 5 DL material model convergence of PO impact category

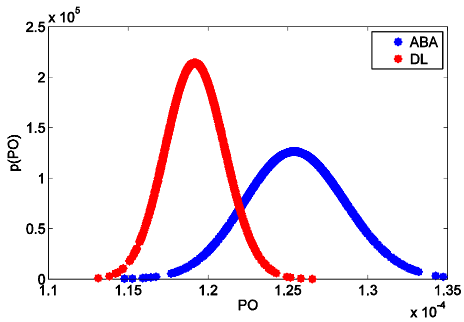
Tab. 1 Means, standard deviations and coefficients of variation of ABA and DL impact assessments calculated through MC approach.

	ABA			DL		
Impact Category	Mean	Std	COV	Mean	Std	COV
A (kg SO2 eq.)	2,25E-3	5,93E-5	0,026	1,57E-3	3,37E-5	0,021
PO (kg C2H4 eq)	1,26E-4	3,14E-6	0,025	1,19E-4	1,87E-6	0,016

In Table 1 it is possible to observe that in the A category, the ABA material is certainly more impacting. However, in the PO category, when observing the standard deviations, there is an interval in which both materials can be the most impacting for the environment. This is confirmed by Figure 6 that shows the lognormal probability density function adjusted to the A and to the PO impact categories' resulting data for both materials. To choose this distribution, some tests were made observing the Maximum Likelihood Estimator of the adjustments through dfittool of Matlab® and the lognormal distribution had the maximum value. Figure 6(b) shows an intersection between DL and ABA probability density functions curves, what confirms that in a certain interval of PO values, both materials can be the most harmful for the environment. However, figure 6(a) excludes this possibility, showing that the ABA panel is always more impacting in the A category.



(a)



(b)

Fig. 6 lognormal probability density function adjusted to the A (a) and to the PO (b) impact categories' data for ABA and DL materials

3.2 Fuzzy data sets

The same example was analyzed through the Fuzzy data sets approach. However, the software Matlab® was used and the starting point was the materials' inventory extracted from SimaPro® including uncertainties: means and standard deviations of each elementary fluid. Each fluid was transformed in a Quasi-Gaussian fuzzy number (Hanss, 2005) expressed by the notation:

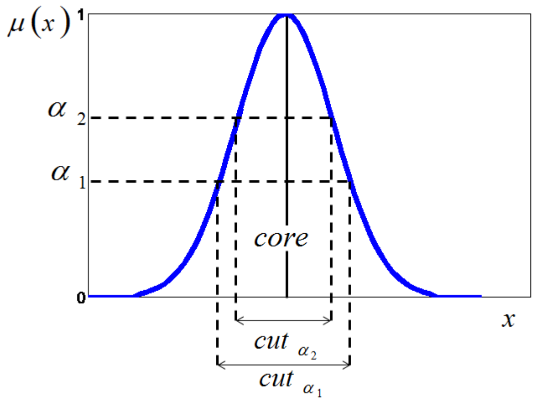
$$\tilde{p} = gfn\left(\bar{x}, \sigma_l, \sigma_r\right) \tag{1}$$

to define a Quasi-Gaussian fuzzy number $\tilde{p} \in \tilde{P}'(\Re)$ with the Membership Function (MF):

$$\mu_{\tilde{p}}(x) = \begin{cases} 0, x \le \bar{x} - 3\sigma_l \\ \exp\left[-\left(x-\bar{x}\right)^2 \big/ \left(2\sigma_l^2\right)\right], \bar{x} - 3\sigma_l < x < \bar{x} \\ \exp\left[-\left(x-\bar{x}\right)^2 \big/ \left(2\sigma_r^2\right)\right], \bar{x} \le x < \bar{x} + 3\sigma_r \\ 0, x \ge \bar{x} + 3\sigma_r \end{cases} \tag{2}$$

where $\bar{x}$ denotes the model value of the fuzzy number and $3\sigma_l$ and $3\sigma_r$ are the left-hand and the right-hand worst-case deviations from the modal value. In this case they are equal to the standard deviation of the elementary fluid, so the function becomes symmetric. This type of fuzzy number was chosen, because its domain is truncated, so it is possible to exclude negative values as well as with the lognormal PDF.

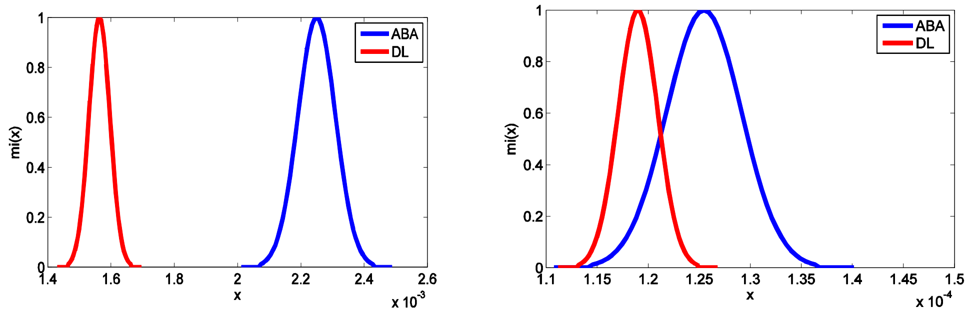
This was a left-right approach of discretized fuzzy numbers where the discretization must be done in function of the membership function, because this curve must contain the number 1 as one of its points which is its maximum and it is related to the mean value of the variable. In the Fuzzy field, each level of the membership function is called $\alpha_N, N = 1.2....$ and the core elements have a degree of membership of unity as observed in Figure 7. All mathematical manipulations described in the schema of Figure 1 to obtain the impact categories fuzzy numbers were made per level and per side (left and right).



Figs. 7 Quasi-Gaussian fuzzy number characterizing $\alpha - cuts$ and core.

In this case study, 30 $\alpha - cuts$ were used in order to obtain a good definition of the Quasi-Gaussian membership function.

Figure 8 shows the resulting membership functions of A and PO impact categories calculated with Fuzzy data sets approach. The same behavior of the MC results was observed, however there is a scale factor that differentiates the PDF's and the MF's. This happens because the PDF's integral over the entire space is equal to one while the MF maximum value is always 1.



(a) (b)

Fig. 8 A (a) and PO (b) impact categories' membership functions for ABA and DL materials

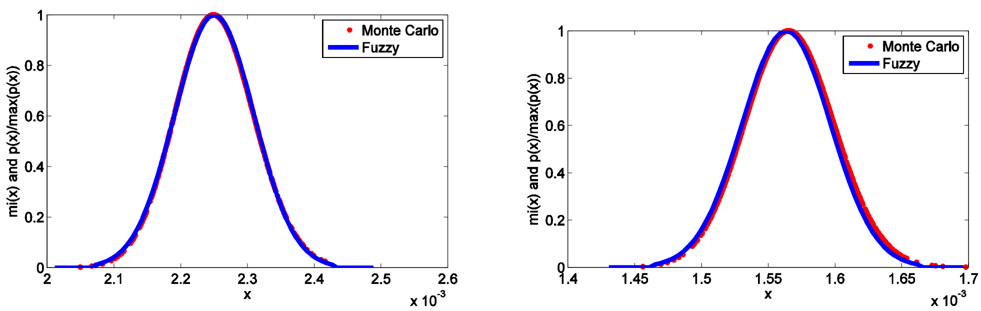
The core values obtained by the Fuzzy approach are displayed in Table 2. It is possible to see that the core values are really close to the mean values obtained by the MC method displayed in Table 1.

Tab. 2 Core values of ABA and DL impact assessments through Fuzzy data sets approach

Impact Category	Core ABA	Core DL
A	2,3E-3	1,6E-3
PO	1,25E-4	1,189E-4

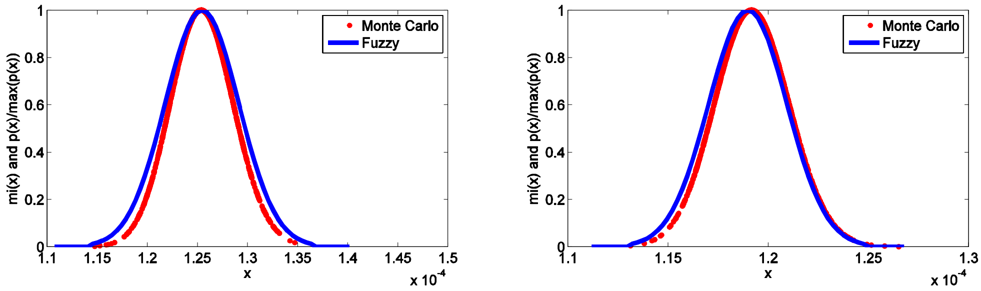
3. Monte Carlo vs Fuzzy data sets

To complete the comparison between MC and Fuzzy data sets approaches, the PDF's curves and the membership function curves of the results were compared. The PDF's were normalized, so they achieved the same scale of the Fuzzy results. Figure 9 shows the comparison for DL and ABA, respectively, for A impact category and figure 10 shows the same results for PO impact category.



(a) (b)

Fig. 9 Comparison between Monte Carlo and Fuzzy approaches for the A impact category for ABA (a) and DL (b) materials.



(a) (b)

Fig. 10 Comparison between Monte Carlo and Fuzzy approaches for the PO impact category for ABA (a) and DL (b) materials.

The similarity of the curves confirms the results' equivalence of the mean and the core values observed in Tables 1 and 2. In the PO impact category, the distances between the curves are higher. For instance, Fuzzy result shows a higher variance in Figure 10(a). This difference is not related to the COV value, because the MC results of Figure 9(a) have the highest COV value (0,026) and they show the best similarity to the Fuzzy results too. It can be related to the distribution of the input data that determines the membership function of the output data in the Fuzzy case and that affects the distribution result in the MC case.

4. Conclusion

This work showed two approaches for the evaluation of input data uncertainty in LCA studies: Monte Carlo and Fuzzy data sets. The first one is a probabilistic approach in which the random variables are modeled, the convergence is analyzed and mean, standard deviation and coefficient of variation of the results are explored. The second one includes the Fuzzy number's modeling, the generation of the membership function according to their discretization, and the left-right approach to obtain the results. Their results were considered equivalent for a simple example of two acoustic materials, in order words, one approach validates the other. It shows that the probabilistic and the possibilistic approaches can be used in order to evaluate the influence of uncertainty in the input data in the results of an LCA model.

This work contributes for the development of the LCA methodology considering uncertainties in the input data; however its utility depends on a good definition of the LCA case goal and scope. If this previous definition includes the evaluation of input data uncertainty and an objective for this analysis, then MC and Fuzzy approaches can be applied and the results and its statistical characteristics will represent the performance of the LCA model and will contribute to its comprehension.

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