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Ignoring correlation in uncertainty and sensitivity analysis in life cycle assessment: what is the risk?

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ABSTRACT

Life cycle assessment (LCA) is an established tool to quantify the environmental impact of a product. A good assessment of uncertainty is important for making well-informed decisions in comparative LCA, as well as for correctly prioritising data collection efforts. Under- or overestimation of output uncertainty (e.g. output variance) will lead to incorrect decisions in such matters. The presence of correlations between input parameters during uncertainty propagation, can increase or decrease the the output variance. However, most LCA studies that include uncertainty analysis, ignore correlations between input parameters during uncertainty propagation, which may lead to incorrect conclusions. Two approaches to include correlations between input parameters during uncertainty propagation and global sensitivity analysis were studied: an analytical approach and a sampling approach. The use of both approaches is illustrated for an artificial case study of electricity production. Results demonstrate that both approaches yield approximately the same output variance and sensitivity indices for this specific case study.
Furthermore, we demonstrate that the analytical approach can be used to quantify the risk of ignoring correlations between input parameters during uncertainty propagation in LCA. We demonstrate that: (1) we can predict if including correlations among input parameters in uncertainty propagation will increase or decrease output variance; (2) we can quantify the risk of ignoring correlations on the output variance and the global sensitivity indices. Moreover, this procedure requires only little data.

1. Introduction

Life cycle assessment (LCA) is an established tool to quantify the environmental impact of a product (Baumann and Tillman, 2004; Curran, 2012; Guinée et al., 2010), and can be seen as a specific procedure within the environmental impact assessment framework (Björklund, 2012; Tukker, 2000). Due to the presence of uncertainty and variability of input parameters in LCA, the need for uncertainty analysis is widely acknowledged (Björklund, 2002; Lloyd and Ries, 2007). However, only a few studies (Finnveden et al., 2009; Imbeault-Tétreault et al., 2013, for example) implemented uncertainty propagation by means of Monte Carlo simulation (Lloyd and Ries, 2007) or performed a sensitivity analysis (Heijungs, 2002; Tukker, 2000; Welz et al., 2011). A reason for this might be that data collection for LCA is perceived as the most time-consuming step (Björklund, 2002). In addition, even if the presence of uncertainty and variability is acknowledged, data might not always be available to construct distribution functions needed for uncertainty analysis.

An additional complication is the potential presence of correlations between input parameters. For example, when both fuel combustion and the corresponding emissions of CO_2 are considered as stochastic input parameters, a correlation might be present between fuel combustion and the emissions of CO_2. Although the amount of CO_2 emissions relates directly to the carbon content of fuel, other (external) factors, such incomplete combustion for low temperatures or quality of the fuel, can cause a presence of a correlation between the two parameters. Currently, in most LCA case studies that include uncertainty propagation, correlations between input parameters are ignored (Björklund, 2002), even though the effect of ignoring these correlations on the output variance is unclear (Bojacá and Schrevens, 2010; Wei et al., 2014). To our knowledge, in only three studies (Bojacá and Schrevens, 2010; Cucurachi et al., 2015; Wei et al., 2014) correlations between input parameters were explicitly included. There can be several reasons why correlations are ignored: (1) there is no data available on the correlation coefficients, (2) including correlation coefficients in uncertainty propagation complicates the

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subsequent uncertainty and sensitivity analysis, which is usually not available in standard LCA software, or (3) unfamiliarity with methods that include correlations during uncertainty propagation.

A good assessment of uncertainty is important for making well-informed decisions in comparative LCA, as well as for correctly prioritising data collection efforts. Under- or overestimation of output uncertainty (e.g. output variance) will lead to incorrect decisions in such matters. For example, ignoring correlations between input parameters in the sample design could lead to under- or overestimation of the output variance. This can lead to incorrect decision making regarding environmental mitigation strategies, or more tangible, to ecological or health risks (Cowell et al., 2002; Tukker, 2002). For example, a common strategy in LCA is to look for improvement options, and to do so, two product alternatives are compared. A suitable approach is to use a *discernibility analysis* (Heijungs and Kleijn, 2001; Henriksson et al., 2015), where random drawings from two Monte Carlo runs are compared and the percentage is given how often one alternative is better than the other. If the output variance of greenhouse gas emissions of a reduction strategy is overestimated due to ignoring correlations between input parameters, this could lead to false negatives. This means the actual variance is lower and the comparison between both products would have led to different results if correlations had been taken into account. Another example concerns the application of a *threshold analysis*, where due to e.g. legal boundaries for ammonia emissions on farms or toxicity levels in soils, a certain threshold may not be exceeded. Ignoring correlations could lead to an underestimation of the output variance and therefore it can appear that the emissions of a product remain under the threshold, while they would have exceeded the threshold if correlation were included.

In this paper, we first present methodology for incorporation of correlation between parameters in modelling of uncertainty propagation and performing global sensitivity analysis in LCA, by using an analytical approach and a sampling approach. After comparing the analytical and the sampling approach, we demonstrated that the analytical approach can be used to quantify the risk of ignoring correlations between input parameters during uncertainty propagation in LCA, based on minimum data requirement. To this end, a hypothetical case study about electricity production is formulated on which the procedure is applied.

2. Methods for uncertainty propagation and global sensitivity analysis for correlated input parameters in LCA

Uncertainty analysis studies the uncertainty of the model output. Subsequently, a global sensitivity analysis can be performed that explains the model output variance (Saltelli et al., 2008). A global sensitivity index represents the sensitivity of each model input parameter and is given by a ratio explaining how much each input parameter contributes to the output variance. For LCAs with uncorrelated input parameters, the squared standardised regression coefficients can be used as a global sensitivity index (Groen et al., 2016; Mutel et al., 2013; Saltelli et al., 2008). For more complicated, non-linear impact assessment methods, advanced methods such as the Sobol' method can be used (Cucurachi et al., 2015).

In case of correlated input parameters in the LCA model, the regression model no longer holds (Xu and Gertner, 2008) and should be adjusted (Xu and Gertner, 2008). In this paper, matrix-based notation for LCA is introduced, followed by the corresponding procedure for uncertainty propagation and global sensitivity indices with correlated input parameters (Xu and Gertner, 2008), for an analytical and a sampling approach. The analytical approach is later on used to determine the effect of ignoring correlation in LCAs.

The MatLab code used in this study is available at: https://evelynegroen.github.io.

2.1. Matrix-based LCA

To facilitate the use of uncertainty and sensitivity analysis, matrix-based LCA is used, where all production processes are described in the **A**-matrix and the accompanying resource use and emissions in the **B**-matrix (Heijungs, 2002). The production processes are represented by $v = 1$ to y columns in the square technology matrix **A** (size $x \times y$), the rows ($u = 1$ to x) represent a specific product flow. For example, if electricity is produced in one column, other production processes given in other columns can use it as input. The inventory matrix **B** (size $z \times y$) consists of use of resources and emissions corresponding to each production process. Using the final demand vector **f** (size x), the production processes are scaled to produce the desired amount. The meanings of all symbols used in this paper are found in Table 1.

To compare the analytic and stochastic approach for correlated input parameters in LCA, first an artificial case study is introduced to show how both approaches work. In this example, we will look at the production of electricity. The production of 10 kWh electricity requires 2 l of diesel. For the production of 10 kWh electricity 1 kg CO_2 is emitted, for the production of 100 l of diesel, 10 kg of CO_2 is emitted. The example is taken from Heijungs (2002). In matrix notation this looks like:

$$\mathbf{A} = \begin{pmatrix} 10 & 0 \\ -2 & 100 \end{pmatrix} \tag{1}$$

The **A** matrix contains three parameters unequal to zero. The corresponding CO_2 emissions can be given by:

$$\mathbf{B} = \begin{pmatrix} 1 & 10 \end{pmatrix} \tag{2}$$