Sensitivity analysis in life cycle assessment

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ABSTRACT

Life cycle assessments require many input parameters and many of these parameters are uncertain; therefore, a sensitivity analysis is an essential part of the final interpretation. The aim of this study is to compare seven sensitivity methods applied to three types of case studies. Two (hypothetical) case studies describing electricity production: one shows linear and another shows non-linear behavior. The third case study describes a large (existing) case study of seafood production containing high input uncertainties. The methods are compared based on their results, i.e. variance decomposition and ranking of the input parameters. Results show that Sobol' sensitivity indices perform the best for all three case studies. The Sobol' method can be a useful method in case of non-linear LCA models or LCA models that include outliers.

Keywords: matrix perturbation, method of elementary effect, key issue analysis, random balance design, Sobol' sensitivity index

1. Introduction

A life cycle assessment (LCA) calculates the environmental impact of a product from cradle to grave. LCAs require many input parameters and many of these parameters are uncertain. A sensitivity analysis, therefore, is an essential part of the final interpretation. This is mentioned in the ISO standards for LCA, but no guidance is given on how to do or how to select an appropriate sensitivity analysis. A sensitive parameter is a parameter of which a change considerably influences the result, or that contributes to the variance of the output. A sensitivity analysis can help identifying parameters that should be known accurately before drawing conclusions, or identifying non-sensitive parameters for which the variance can be fixed in the region of its variance in order to simplify a model, also known as 'factor-fixing' (Saltelli et al. 2008).

Sensitivity analysis in LCA can be performed using a one-at-a-time approach (OAT), meaning that a subset of the input parameters are changed one at a time to see how much influence it has on the results. Although this approach has many advantages, e.g. it is easy to perform and to understand, this type of sensitivity analysis is time-consuming for a large system and might not consistently take all parameters into account and, therefore, could overlook possible sensitive parameters. Sensitivity analyses that consistently analyze the sensitivity of each parameter in the model are usually performed with sampling based approaches, such as Monte Carlo simulation, with an added procedure for variance decomposition.

In general we can differentiate between three types of sensitivity analysis: local sensitivity analysis (e.g. OAT); screening (e.g. method of elementary effect) and variance based sensitivity analysis or global sensitivity analysis (e.g. regression analysis). An overview is given in Table 1. The methods differ in their input requirements (e.g. knowledge about probability distribution function and parameter of dispersion) and type of output: either a ranking and/or variance decomposition of the input parameters.

Table 1. Types of sensitivity methods discussed in this paper.

Type	Method
Local	Matrix perturbation (MP); one-at-a-time approaches (OAT)
Screening	Method of elementary effect (MEE)
Global	Standardized regression coefficients (SRC); key issue analysis (KIA); random balance design (RBD); Sobol' indices (SME and STE)

For most of the sensitivity methods mentioned in Table 1, it is not yet known under which conditions they optimally perform, or if they can outperform the standard practices in LCA (i.e. OAT, MP, SRC, KIA). The aim of this study is to compare seven sensitivity methods applied to three types of case studies: one showing linear, another showing non-linear behavior and a large linear case study, but with large input uncertainties. The methods are compared based on their performance i.e. variance decomposition and ranking of the input parameters

2. Methods

2.1. Case studies

In this study we applied the sensitivity methods to two case studies of the production of 1 MWh electricity (the original version of the case studies appeared in (Heijungs 2002; Heijungs and Suh 2002). Both case studies consisted of two processes: fuel production and electricity production. The first case study produces electricity thereby using fuel (figure 1). In the second case study, electricity is in turn necessary for fuel production, creating a loop (figure 2). The parameters of the second case study are known to be locally (very) non-linear (Heijungs 2002). For both case studies we assumed that each input parameter is normally distributed with a standard deviation equal to 10% of the mean. Furthermore we assumed that the parameters are uncorrelated and independent. For both case studies the parameters are numbered as follows: 1 (production of electricity); 2 (use of fuel for electricity production); 3 (use of electricity for fuel production, which is zero in the first case study); 4 (production of fuel); 5 (emissions of CO_2 during electricity production); and 6 (emissions of CO_2 during fuel production).

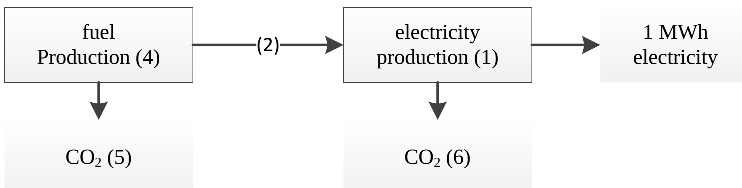

Figure 1. Case study 1: production of 1000 kWh electricity requires 200 liter fuel.

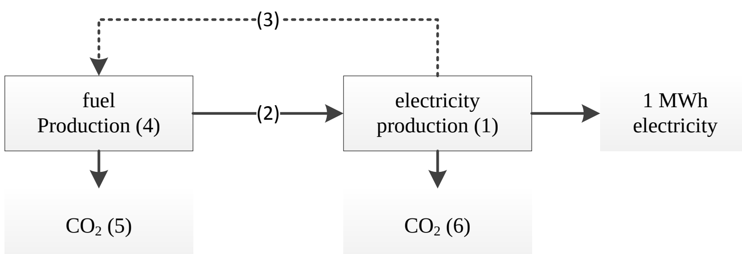

Figure 2. Case study 2: production of fuel requires electricity.

The third case study describes a trawler operating in the Northeast Atlantic, targeting mainly cod and haddock. The case study consists of 115 input parameters, describing e.g. production of vessel and gear, fuels, anti-fouling and cooling agents (figure 3). We assumed that the input parameters come with high uncertainty, each standard deviation of each parameter varies with 30% of the mean. All parameters are log-normally distributed.

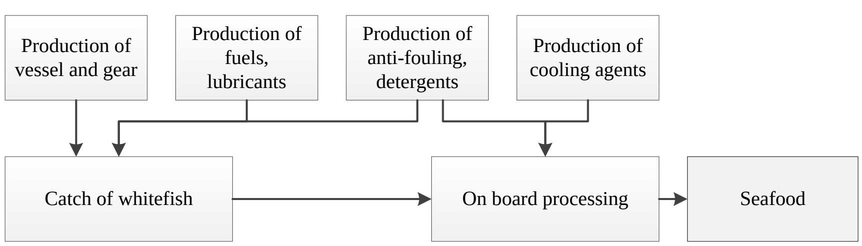

Figure 3. Case study 3: production of seafood.

The trawler takes trips of about ten to fourteen days, landing its catch in Tromso, Norway. The functional unit consists of 1 tonne landed whitefish.

2.2. Methods for sensitivity analysis

2.2.1. One-at-a-time

One-at-a-time (AOT) approaches take a subset of the input parameters, which are changed one at a time (either within its range or using an arbitrary value) to see how much influence it has on the result. The method is easy to perform and to understand, but this type of sensitivity analysis is time-consuming for a large system and, therefore, might not consistently take all parameters into account and could overlook possible sensitive parameters.

2.2.2. Matrix perturbation

Matrix perturbation (MP) as a method of (local) sensitivity analysis was introduced in LCA by Heijungs and Suh (2002). MP makes use of the first order partial derivatives as estimators of local sensitivity, which can be converted into relative multipliers. If the multiplier is larger, a change in the input parameter will change the result more than when the multiplier is almost zero. Information such as the type of distribution function or parameter of dispersion is not used. The result of this method shows how much the results will change if the input parameters are slightly changed (perturbed). This means that the multipliers predict the magnitude and direction of the change in the result of a small change around the original value of each parameter. A disadvantage of applying MP is that the method considers the model in its current configuration, and therefore the result (in general) only holds for small changes around the original parameter values. Moreover, information on which input parameter is quite certain and which is not (i.e. of the ranges of the parameters), is not used.

2.2.3. Method of elementary effects

The method of elementary effects (MEE) is a screening method that was originally designed by Morris (1991) and adjusted by Campolongo et al. (2007). MEE has been applied in LCA by Mutel et al. (2013) and de Koning et al. (2010). In order to apply MEE the ranges of the individual parameters are taken into account, where a range is defined as the upper and lower boundary of an input parameter. MEE can be seen as an extended one-at-a-time approach (Saltelli et al. 2008). MEE combines alternative values of each parameter (at predefined proportional steps in the range defined) and calculates the result. The difference between the original model and the new result of each combination is the elementary effect. Another indicator that can be calculated is the standard deviation of the elementary effect, which is an indicator for the interaction or non-linear effects: if the elementary effect of a certain parameter changes considerably for each run, the magnitude of the elementary effect depends on either the configuration of the model or the presence of nonlinear effects. MEE can be used as a precursor to the more computationally demanding sampling methods as regression. A disadvantage of this method is that the results are not an estimation of the actual variance decomposition.

2.2.4. Key issue analysis (Taylor expansion)

Key issue analysis (KIA) was introduced in LCA by Heijungs (2002) as a method for (analytically) determining the contribution to variance (or variance decomposition) by means of a first order Taylor expansion. KIA has been applied in LCA for example by Heijungs and Huijbregts (2004) and Heijungs et al. (2005). It combines the steepness of a function (described in section 2.2.1 above) with the variance of the individual parameters. KIA calculates the variance decomposition up to first order (or "main effects"), as covariance between input parameters are mostly unknown (Heijungs, 2002). To apply this method only the variances of the individual parameters are used. A disadvantage of KIA is that it does not produce a distribution function of the output, making it more difficult to compare two or more studies.

2.2.5. Standardized regression coefficients (using Monte Carlo sampling)

Standardized regression coefficients (SRC) are obtained from the slope of the line from least square fitting and estimate the contribution to output variance for each input parameter. Pseudo-random samples are taken from all input parameters and for each run the output is calculated. Subsequently, for each input parameter the regression coefficient is calculated; the coefficients are standardized with respect to their standard deviation. An advantage of calculating SRC is that it is commonly applied (in and outside) LCA, a disadvantage is that many runs are needed to calculate the variance decomposition.

2.2.6. Random balance design

The foundation of random balance designs (RBD) are from Cukier et al. (1978). In this study we use the format similar to Tarantola et al. (2006). RBD has been not yet been applied in LCA to our knowledge, although a very closely related method Fourier amplitude sensitivity test, has been applied by de Koning et al. (2010). Random balance designs estimate the contribution to variance by using Fourier transformations. A periodic sampling is applied and for each input parameter the Fourier spectrum is calculated, which is an estimate for the first order sensitivity index. A disadvantage of RBD is that only the main effect can be calculated.

2.2.7. Sobol' sensitivity index

The method by Sobol' (2001) assigns a sensitivity measure to each input parameter by calculating how much of the output variance can be allocated to each input parameter. The idea of the method is that a model can be decomposed into terms of increasing order, where the first order terms, also called the Sobol' main effects (SME), are equal to the contribution of variance caused by each input parameter to the output variance (Saltelli et al. 2010). The method also allows calculation of the interaction effects (variance caused by varying two or more parameters simultaneously) and the total effect index. The Sobol' total effect index (STE) gives the variance caused by the sum of the main and interaction effects of an input parameter. A disadvantage of Sobol's method is that many runs are needed to calculate the indices; hence the model is computationally expensive.

3. Results

3.1. Results of local methods

First the results of the local methods are presented, because it is not accurate to compare local with global methods, as they do not display similar information. Global sensitivity methods (or variance-based methods) include uncertainty information such as the variance into their results, while local methods estimate the change in the outcome based on the configuration of the (LCA) model at hand. The ranking of parameters by applying the local methods can be found in Table 2.

Table 2. Ranking of the parameters of the local methods for case study 1, 2 and 3, e.g. parameter 1 is most sensitive for case study 1 and 2. OAT: one-at-a-time approach; MP: matrix perturbation. The meaning of the parameters of case study 1 and 2 can be found in figure 2. FE: fuel use; EP: emission factor of fuel production; FP: fuel production; EC: emission factor of fuel combustion; LF: landed fish.

	Case study 1		**Case study 2**		**Case study 3**	
Rank	**OAT**	**MP**	**OAT**	**MP**	**OAT**	**MP**
1	1	1	2	1	LF	LF
2	5	5	1	2, 4	EC	EC
3	2	2, 4, 6	3	3	FP	FP
4	6		4	5	EP	EP
5	4		5	6	FE	FE
6			6			

For case study 1 both methods give similar results. For case study 2 the results differed slightly, although the actual values for parameter 1 to 4 were very close for both methods. Case study 3 gives also similar results.

3.2. Global methods: case study 1 electricity production

Applying the global methods to the first case study showed that the ranking of the input parameters were (almost) similar for each method (Table 3). The variance decomposition is given between brackets, but cannot be calculated for MEE as this method only gives a ranking of parameters. For example, in case of applying KIA parameter 1 is responsible for 56% of the output variance.

Table 3. Ranking of the parameters for case study 1, e.g. parameter 1 is most sensitive. MEE: method of elementary effect; KIA: key issue analysis; SRC: standardized regression coefficient; RBD: random balance design; SME: Sobol' main effect index; STE: Sobol' total effect index.

Rank	**MEE**	**KIA**	**SRC**	**RBD**	**SME**	**STE**
1	1	1 (56%)	1 (57%)	1 (58%)	1 (53%)	1 (58%)
2	5	5 (39%)	5 (37%)	5 (40%)	5 (33%)	5 (38%)
3	2	2, 4, 6 (1.6%)	2 (1.7%)	6 (2.5%)	4 (3.8%)	2 (1.7%)
4	6		6 (1.6%)	2 (2.4%)	2 (3.1%)	6 (1.6%)
5	4		4 (1.5%)	4 (2.1%)	6 (2.4%)	4 (1.6%)

KIA required only a single calculation, which means (in case of LCA) that these methods are computationally very fast. MEE required relatively few runs compared to the other sampling based methods. SRC, RBD and the Sobol' indices made use of sampling, SRC and the Sobol' indices requiring the largest number of runs. Although the individual contributions differed between methods, the overall picture is the same.

3.3. Global methods: case study 2 electricity production

Applying the methods to the second case study, we found that SRC, RBD and SME did not give reasonable results (Table 4), all parameters showed a contribution of about 0%. Although the ranking of the parameters is somewhat different, it should be noted that the difference in sensitivity between parameter 1, 2, 3 and 4 were very small in case of MEE and KIA (Table 4). Only the Sobol' total index (STE) explicitly indicated parameter 3 as begin responsible for most of the output variance. The variance decomposition given by KIA and STE are given in Table 4 (SRC, RBD and SME are not shown as they did not gave reasonable results). KIA shows the main effects, indicating that parameter 1-4 are responsible for 25% of the output variance, the STE shows that, taking all interaction into account between, e.g., parameter 3 and the other parameters in the model, that parameter 3 is responsible for almost 93% of the output variance.

Table 4. Ranking of the parameters for case study 2. MEE: method of elementary effect; KIA: key issue analysis; SRC: standardized regression coefficient; RBD: random balance design; SME: Sobol' main effect index; STE: Sobol' total effect index.

Rank	**MEE**	**KIA**	**SRC**	**RBD**	**SME**	**STE**
1	3	1 (25%)	-	-	-	3 (93%)
2	4	2, 3, 4 (25%)				2 (50%)
3	2	5 (0%)				4 (50%)
4	1	6 (0%)				1 (50%)
5	5					5 (0%)
6	6					6 (0%)

3.4. Global methods: case study 3 production of seafood

Applying the global methods to the third case study showed that the ranking of the input parameters were (almost) similar for each method (Table 5), just as for case study 1. The five most sensitive parameters are shown, that contribute more than 1% to the output variance. The variance decomposition is given between brackets.

Table 5. Ranking of the parameters for case study 3. MEE: method of elementary effect; KIA: key issue analysis; SRC: standardized regression coefficient; RBD: random balance design; SME: Sobol' main effect index; STE: Sobol' total effect index. FE: fuel use; EP: emission factor of fuel production; FP: fuel production; EC: emission factor of fuel combustion; LF: landed fish.

Rank	MEE	KIA	SRC	RBD	SME	STE
1	LF	LF (56%)	LF (46%)	LF (51%)	LF (55%)	LF (59%)
2	EC	EC (41%)	EC (38%)	EC (36%)	EC (38%)	EC (41%)
3	FP	FP (~1%)	FP (~1%)	FP (~1%)	FP (~1%)	FP (~1%)
4	EP	EP (~1%)	EP (~1%)	EP (~1%)	EP (~1%)	EP (~1%)
5	FE	FE (~1%)	FE (~1%)	FE (~1%)	FE (~1%)	FE (~1%)

An interesting difference with case study 1, now that we have increased the uncertainty of the input parameters, is that STE is able to explain more of the variance than SME. SRC underestimates the contribution of parameters LF compared to the other methods. The sum of SRC, RBD and SME equals approximately 90%, indicating that the LCA model contains outliers. The sum of the variance decomposition according to KIA however, still sums up to 100% and does not show the presence of outliers.

4. Discussion

We did not take correlations between input parameters into account. If correlations are not taken into account, the result of the variance decomposition might be over- or underestimated. Nevertheless, we think that the results in this paper will also hold for LCA models containing correlated input parameters.

5. Conclusion

The results of a sensitivity analysis in LCA are important because they can be used to identify parameters that can considerably change the result, and which might need further investigation. They can also be used to identify parameters that are responsible for most of the output uncertainty and therefore should be known accurately before presenting results. Based on this study, we prefer the use of matrix perturbation in case of assessing the local sensitivity as it is more consistent than OAT where only a subset of the input parameters can be analyzed. MEE is a useful method in case of large models as a precursor to more computationally expensive sampling based methods. In case of interest in variance decomposition, we recommend the use of the Sobol' sensitivity indices in combination with KIA. Sobol' indices allow the calculation of main, interaction and total effect indices and the total index can also be calculated when the case study at hand shows non-linear behaviour. When the LCA practitioner is only interested in the main effect in case of a linear case study, KIA can be used.

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