Uncertainty and variation in LCA - Implementation of probabilistic methods to assess environmental impacts of infrastructures

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- Implementation of probabilistic methods to assess environmental impacts of infrastructures

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Preface

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Summary

For most applications trying to interpret the real world uncertainties will be an important factor to consider, which is also true for Life-Cycle Assessment used for estimating total environmental impact during the life-cycle of products, services, buildings, structures, roads etc. The construction and usage of infrastructure are major causes of emissions and energy use, thus making it even more important for society to aim at reducing this impact. One way of reducing environmental impact is by using LCA to show improvements for specific items and/or benefits of using a specific solution over another.

To be able to use LCA, or any other calculated estimation, for comparisons it is of great importance to incorporate effects of uncertainties and to understand where such uncertainties have their sources. Otherwise, any attempt on comparing two solutions will be flawed and there is a risk for bias towards a specific solution.

The aim of the work presented in this report have been to describe and discuss the types of uncertainties present in a LCA, and to discuss their importance, source and influence. An extensive review of the current state of the art of both uncertainties in general and specifically for LCA have been performed to find the most common ways of including uncertainties in LCA, with focus on the possibilities and limitations of different types of methods.

It was found that many previous attempts on including uncertainties in LCA exists, and they showed that it is now possible to using probabilistic methods such as Monte Carlo simulations to incorporate uncertainties in LCA-tools, since the computational capacity have increased. The common problem for all previous studies and the study presented here is the availability of validated input data including uncertainty estimations. Initiatives exist for data quality control; however, they do not fully consider the effect of uncertainties, and typically have been limited to the consideration of variations in emission factors only. Other factors such as system boundaries and choices made by the user have a much larger influence on the result than a small variation in the emission factor itself.

To evaluate this, the basis for a methodology considering uncertainties in LCA and possibilities for controlling these uncertainties is presented. The methodology is based on general definitions of uncertainties to be able to understand the source and characteristics of each affecting parameter and for making informed decisions on how to reduce the uncertainty depending on the purpose of the LCA. This kind of methodology will especially be valuable for raising awareness of uncertainties in LCA for different stages of the building process.

The possibility of including uncertainties in a LCA-tool for infrastructures in also presented, showing possibilities for studying the sensitivity of the input parameters and the propagation of uncertainties. A case study is used to demonstrate these possibilities, showing the importance of considering uncertainties in all input parameters. It is shown that the influence of other factors apart from the emission factors can be large, such as material amounts and expected service life, and that they have to be considered if reasonable results are sought. It should be noted, however, that the case study presented in this report serves illustrative purposes and includes significant simplifications.

Contents

1 Introduction

1.1 Background

Decisions on investments concerning large infrastructures involve the consideration of several aspects such as costs during different phases of construction and asset management, societal benefits expected by the services the infrastructure provides, impacts on the environment, safety of users, sustainability and resilience etc. The various costs related to operation, maintenance and demolition can be expressed in monetary units and considered using a cradle-to-grave approach with Life Cycle Cost (LCC) methodology. However, besides the costs of resources committed to different phases of the project, environmental and social impacts can also be significant. To put a "price tag" on these issues is more difficult and involves large uncertainties.

The transportation network uses energy and impacts the environment, both due to emissions from traffic and emissions from construction, operation, utilization and maintenance and deconstruction of the infrastructure. Large infrastructure projects use resources intensively and contribute significantly to emissions of greenhouse gases (GHG) by using large amounts of fossil fuels, concrete, steel, bitumen etc. during construction. Another large part of the environmental impact from the infrastructure comes from the operation and utilization phases (mainly lighting, and fuel consumption). Environmental impacts of transport infrastructure are often assessed throughout the entire life cycle utilizing Life Cycle Assessment (LCA) (Stripple, 2001; Stripple and Erlandsson, 2004). A standardized framework for LCA is given in ISO 14040 (2006) and ISO 14044 (2006).

To be able to estimate the environmental impact of infrastructures, practical methods and tools are needed, since the number of variables often are large. One such example is a tool used by the Swedish Transportation Administration (Trafikverket), Klimatkalkyl, that can, to some extent, estimate the climate impact and required energy of the infrastructure using LCA methodology (Toller and Norberg 2017). Other tools and programs are also available such as e.g. GaBi (Thinkstep 2018), SimaPro (SimaPro 2018) and SULCA (VTT 2018).

In order to make a proper comparison using LCA, the system boundaries must be similar. Preferably, the assessment should be made from cradle-to-grave, i.e. from construction phase, through operation, maintenance and utilization until disposal. However, the system boundaries are often drawn to include construction, operation and maintenance only, using a cradle-to-gate approach (Figure 1). The reason of not including disposal is that it is unlikely that transport infrastructure is completely demolished, while the utilization phase is normally not included due to the technical differences between traffic and the actual structures. The problem with excluding the utilization phase is that further considerations, such as fuel consumption and financial responsibility, are neglected. Furthermore, in some cases such as in Klimatkalkyl, impacts due to transports are also neglected, where transports refer to the transportation from the production of the components and products to the site, while in other tools and calculations the impact of transports is included. This confirms the importance of consistent system boundaries, since this difference may lead to differing LCA-results.

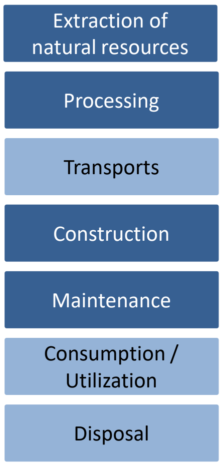

Figure 1 Conceptual chart of Life Cycle Assessments in Trafikverkets Klimatkalkyl (boxes marked with lighter colour are normally not included) (Toller and Norberg 2017).

Another problem is that these tools for estimating environmental impacts use extensive input data from sources with varying reliability and include several assumptions. The results are often used to compare and choose between alternatives and support decisions. Therefore, important information for the decision maker would be the quality of the result, i.e. the uncertainty of the prediction.

Uncertainty and variability is present at all stages of an LCA. Some uncertainties arise from lack of knowledge on the true value of a quantity and can be reduced by more research and efforts to find better data and by estimating the validity of and uncertainties in the results. Other variation on the other hand stems from the natural heterogeneity of values, such as natural variations between geographical locations or variations over time.

Another difficulty when predicting environmental impacts is the level of complexity in the calculations. Since the amount of input parameters is large, due to the complexity of the environment itself, it is necessary to have a high level of detail in the LCA-tool. However, for practical applications, limitations and boundaries have to be defined and different models will therefore have different levels of complexity, which will affect the validity and reliability of the outcome and introduce new uncertainties. Thus, the complexity of different levels of abstraction within one model needs to be consistent with the purpose of the investigation. This is summarised by Elms as the "principle of consistent crudeness", which states that the quality of the output of a model is dominated by the quality of the crudest input or of the model itself (weighted according to the sensitivity of the output to that input) (Elms 1985).

The increased focus on environmental impact and energy use have led to governmental regulations and target reduction levels. In Sweden this has led to a regulation for the Swedish Transportation Administration (Trafikverket), where demands are set on mandatory reduction of CO_2-equivalent emissions of 17-30 % for infrastructure projects, depending on the completion year, compared with the emission level by 2015 (Trafikverket 2017). The question then arises on how reliable the reference level is and on how we can be certain that a suggested reduction really meets the demands? As of now, when no consideration of uncertainties is included in Klimatkalkyl and other tools, the reference values has to be conservative enough to consider all possible outcomes. A comparison will also be difficult to assess without considering uncertainties, and the shown reductions may be irrelevant and difficult to verify.

1.2 Purpose, objectives and scope

The main purpose of this report is to show the importance of considering uncertainties when performing life cycle assessment (LCA) for of infrastructure assets and to give an overview of the possibilities and limitations. The main objectives of the report are to:

- Illustrate the benefits and limitations of including uncertainties on the validity of results for calculations of environmental impacts by
    - Providing an overview of possible methods for including uncertainties in LCA;
    - Explaining the importance and effect of uncertainties;
    - Giving a state of the art concerning methodology for including uncertainties.

- Propose a methodology for reducing uncertainties related to processes included in infrastructure LCA by
    - Categorising and understanding the type of uncertainties involved;
    - Demonstrate methods for including uncertainties in a LCA-tool;
    - Demonstrate how the proposed methodology may be applied.

Due to limitations in available uncertainty data for LCA-applications, no actual uncertainty values are used in the calculations. The report will instead focus on the possibilities and effects on the results when uncertainty analysis is included with generic uncertainty values assigned. This lack of reliable input data is, in itself, a major uncertainty that will be discussed in later chapters of the report.

2 Notations

Below follows a list of used notations and abbreviations in the report.

ANOVA	Analysis of Variance
c	Sensitivity factor
CED	Cumulative Energy Demand
CO	Carbon-oxide
CO_2	Carbon-dioxide
COV	Coefficient of Variation
EPD	Environmental Product Declaration
GHG	Green House Gases
GSA	Global Sensitivity Analysis
GWP	Global Warming Potential
ILCD	International Reference Life Cycle Data System
LCA	Life Cycle Assessment
LCC	Life Cycle Cost
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
OAT	One At the Time
PCR	Product Category Rules
S	Sensitivity coefficient
σ	Standard deviation
VMEA	Variable Mode and Effect Analysis

Other notations are also listed in the Appendix, these will however not appear in the other parts of the report.

3 LCA – an overview

A system analysis is a tool that allows a product to be analysed through its entire life cycle, from raw material extraction and production, via the material's use to waste handling and recycling. The most common tool for system analysis of environmental impacts is the Life Cycle Assessment (LCA) methodology. The LCA methodology is described in, for example, the standards EN ISO 14040 (2006) and 14044 (2006). In a life cycle assessment, a mathematical model of the system is designed. This model is of course a representation of the real system, including various approximations, assumptions, variations and uncertainties.

The LCA models are built up of different equations. Basically, one can distinguish between models with single equations for each process module calculated per performance unit for that specific process module and models that are based on an equation system for the entire model. The equation system gives several advantages, e.g. better possibilities for recycling flows (loops), but is often limited to linear equation systems. The results from the model are then dependent on the values and assumptions in the model and the model results are valid for these values and assumptions. The LCA methodology allows us to study complex systems, where interactions between different parts of the system exist, to provide as complete a picture as possible of the environmental impacts of, for example, a product.

An LCA is usually made in three steps with an additional interpretation step, see ISO standard. In the goal and scope definition, the model and process layout are defined, along with a specification of the functional unit which is the measure of performance that the system delivers. In the Life Cycle Inventory analysis (LCI), the material and energy flows are quantified, where each sub-process has its own performance unit and several in- and out-flows. The processes are then linked together to form the mathematical system being analysed. The final result of the model is the sum of all in- and out-flows calculated per functional unit for the entire system.

The life cycle impact assessment (LCIA) is defined as the phase of life cycle assessment aimed at understanding and evaluating the magnitude and significance of the potential environmental impacts for a product system throughout the life cycle of the product. The impact assessment is performed in consecutive steps including classification, characterization, normalization and weighting. The LCIA phase also provides information for the life cycle interpretation phase, where the final environmental interpretation is made. In many cases, only classification and characterization are performed due to the uncertainty of the methodology for normalization and weighting. As shown above, not only the value of the different parameters used in the model can vary but also the model itself (model layout, calculation strategies, scope and coverage of the model, impact assessment method, methods for normalization and weighting etc.). This indicates that an uncertainty calculation can be very complex and include many different types of uncertainties. It is thus important to distinguish between different types of uncertainties and variations, and to establish control over the calculations of uncertainties and to define its purpose and goal.

4 Uncertainty and uncertainty analysis

This chapter gives general descriptions of uncertainty and related analysis methods. For more information, see e.g. Blom (1989), Benjamin and Cornell (2016), Cacuci (2003). Several of the statistical terms and concepts used in this report can be found in Appendix A.

4.1 Uncertainties – general definitions

Consideration of uncertainties and variations has become important parts of our current view on how we perceive the real world around us on how we make judgements and decisions. When predicting the outcome of processes, besides random variation, other sources of uncertainty will influence the prediction including e.g. model errors, parameter uncertainties, and human mistakes. These various types of uncertainties may be classified in different ways, see e.g. Ditlevsen & Madsen (1996).

One possible classification is to distinguish between aleatory and epistemic uncertainties. The former refers to the underlying, intrinsic uncertainties, e.g. the scatter in the output of production processes within a population of suppliers. The latter refers to the uncertainties due to lack of knowledge, uncertainties that can be reduced by means of collecting additional data or information, better modelling and better parameter estimation methods.

In statistical modelling, the main focus is on three kinds of uncertainties (Ditlevsen and Madsen, 1996), namely:

- Random variation or physical uncertainty, i.e. the uncertainty identified with the inherent random nature of a phenomenon, e.g. the variation geometrical dimensions of supposedly identical components of bridge. Sometimes also called scatter, randomness or noise.
- Statistical uncertainty, i.e. the uncertainty due to statistical estimation of model parameters based on available data, e.g. the estimation uncertainty of parameters in a regression model describing emission levels as a function of certain product property. Generally, observations of the realizations of a random variable do not represent it perfectly and as a result there may be bias in the data as recorded. Furthermore, different sample data sets will produce slightly different statistical estimates.
- Model uncertainty, i.e. the uncertainty associated with the use of simplified relationships to represent the real characteristic of a given phenomenon, e.g. how different factors contribute to emissions in an LCA calculation is only a model of the real processes resulting in emissions. Modelling uncertainty is often a result of lack of knowledge and can be reduced with improving the understanding of the underlying phenomena and available information.

The first type of uncertainty, random variation, is clearly an aleatory uncertainty, whereas the others should be regarded as epistemic uncertainties, as they can be reduced through better knowledge. Various types of uncertainties valid for LCA purposes are described more in chapter 5.

4.2 Uncertainty analysis methods

4.2.1 General

Several methods exist for the analysis of uncertainties. From a statistical modelling point of view, the choice of model complexity can be categorized as a first moment, a second-moment or a full probabilistic model.

Here, a brief review of the different levels of methods is given, focusing on describing assumptions, advantages and disadvantages of each method. For more details on the methods, see e.g. Ditlevsen & Madsen (1996). Later on, we will discuss what statistical model complexity is suggested for LCA and some specific methods and techniques will be introduced.

4.2.2 First-moment methods

In first-moment methods, only the first statistical moments, i.e. the mean values are considered. Therefore, first-moment methods do not consider any uncertainties. Typically, life cycle assessments of infrastructure projects are deterministic calculations of environmental impacts, and thus do not provide information about the uncertainties associated with the final results. One way to provide such information, at least at some extent, is to systematically analyse the changes in each parameter, i.e. the sensitivity of the outcome with regard to the studied variable.

4.2.3 Second-moment methods

Second-moment methods include the variances of the actual variables in the calculation, as opposed to the first-moment method where only mean values are considered. Since the second-moment method takes both the mean value and the variance into account in a rational way, it is a large step towards a relevant probabilistic result compared to a first-moment method. However, it is simple enough to be used even for very complex physical relationships. Caution is needed when the response function is highly non-linear and a linear approximation may result in large errors, e.g., in cases of periodic components, strong interaction effects or higher-order terms. However, in many cases, a simple transformation of the response makes the linear approximation more reasonable.

One second moment method is The Variation Mode and Effect Analysis (VMEA), which can be used to investigate the effect of uncertainties and identify critical areas for reducing unwanted variation (Chakhunashvili et al., 2004; Johansson et al., 2006; Johannesson et al., 2013).

In the concept development phase, VMEA is useful for identifying sources of variation and establish the possible knowledge about them. In VMEA, both uncertainty and variability can be considered and it uses only the standard deviation to characterize the distribution of the uncertainty sources. Furthermore, it is first order since it uses a linear model with use of sensitivity factors.

The VMEA method is based on characterizing each source by a statistical standard deviation and calculating its sensitivity with respect to the target function. The VMEA method combines these into the total prediction uncertainty, denoted τ, which is obtained by the root sum of squares of the uncertainties:

$$\tau = \sqrt{\tau_1^2 + \tau_2^2 + \tau_3^2 + \cdots + \tau_i^2} = \sqrt{c_1^2\sigma_1^2 + c_2^2\sigma_2^2 + c_3^2\sigma_3^2 + \cdots + c_i^2\sigma_i^2} \quad (1)$$

where τ_i is the resulting uncertainty from source i and is calculated as the product of the sensitivity coefficient c_i and the uncertainty σ_i of source i.

The relationship between a target variable Y and an uncertainty source X can analytically be described by the function $Y = f(X)$. For example, the target Y could be the emission produced by constructing a certain bridge component, whereas an uncertainty source X is a quantity of concrete needed for the construction of that specific component. The sensitivity c of Y to X can be expressed as the first derivative of the function f:

$$c = \frac{df}{dX} \quad (2)$$

The sensitivity determines how much of the uncertainty that is transferred to the target variable and it will depend on the point, μ_x, at which it is calculated.

The uncertainties in VMEA are quantified using the standard deviation of the uncertainty source. The assessment can be based on expert judgement, e.g. by estimating the variation range of a parameter, which is translated into a standard deviation σ. Another approach is to judge the uncertainty directly in terms of relative uncertainty, i.e. in terms of percentage uncertainty.

The implementation of VMEA is easy; since no probabilistic function definitions are needed. The input information uncertainty is reduced to a minimum, i.e. to a scalar measure of the standard deviation of each source. The total uncertainties can then be calculated analytically, thus no special software is required (simple Excel spreadsheets can be used).

4.2.4 Full probabilistic methods

In a full probabilistic approach, higher moments of the variables are included, i.e. a full representation of the probability distribution of each variable is used. Such an approach could be beneficial e.g. in LCA calculations as it gives a complete description of related equations and parameters and will also provide a distribution for the result or output possible to use in subsequent analyses.

Unfortunately, there is a strong limitation on the use of such methods, since the exact distributions of the input variables are usually not known. Without proper knowledge, the input distributions must be constructed by subjective choices, and the output might give results with false accuracy. Furthermore, this approach is computationally more demanding than the lower level methods. However, several advanced sampling algorithms exist to reduce the required amount of computation.

The most common method for full probabilistic approaches is the Monte Carlo simulation, which is a technique that consists of generating a large number of virtual samples based on random cumulative distributions. Based on the distribution, stochastic parameters and importance of each input variable, it is possible to get information on the mean and variability of the results. The main benefit of this method is that it is possible to get statistical estimates of the output, e.g. in our case information on the uncertainty in the result. A drawback is that information on the input variables concerning their uncertainty is needed. This, however, is, as stated earlier, a common problem for all possible methods for including uncertainty in LCA-calculations, since it is difficult to find uncertainty data for input variables.

Another problem with using Monte Carlo simulations is the number of simulations needed for convergence. In most cases, more than 10000 simulations are needed for finding a reliable result. For a calculation with a small number of parameters, this is not a significant issue, since it will not take much time, but for more complex problems and calculations with a large number of parameters, as in many LCA applications, this may give very long simulation times.

Sampling methods exist for reducing simulation time, some popular ones are:

- Latin Hypercube sampling
- Importance sampling
- Directional simulation
- Adaptive sampling

For more information regarding these sampling techniques, see e.g. Melchers (1999), Kroese et al. (2011).

With the development of faster computers, the possibility for using full Monte Carlo simulation have increased and is widely used today. In the case study presented in chapter 7 in this report, only full Monte Carlo simulation is used, since the examples are limited in scope and thus suitable for full simulations.

4.3 Uncertainty propagation

Once the uncertainties of the original data are determined, the data are used in the mathematical model, which for LCA consists of mathematical equations or equation systems. When the input data with its corresponding uncertainties are used in the equations, both the values and the uncertainties are calculated in the models. The uncertainties from the original data will thus propagate in the model equations to a final uncertainty.

Assume two variables x and y with its corresponding uncertainties Δx and Δy. From these variables, the resulting variable z with its uncertainty Δz can be calculated by using mathematical rules. In Table 1, some mathematical rules are summarised; the rules assumes as large uncertainty interval as possible, a worst case scenario. The table shows how uncertainties propagate in some basic calculations (addition, subtraction, constant multiplication, multiplication and division, product of powers, and a general method for functions). More information regarding uncertainty propagation can be found in e.g. Berendsen (2011).

As most LCA models are based on linear equations or linear equation systems, the equations for uncertainty propagation found in Table 1 can be considered as the most important for the understanding of uncertainty propagation in LCA. In the same way as above, the uncertainty propagation can be calculated for many different functions. The table below only shows some examples. The last row in Table 1 shows a general way of calculating the uncertainty propagation.

Another source of uncertainty propagation is related to the communication of results, data and figures (Berendsen 2011), for LCA and other processes. In the communication of different figures, different information is transferred. The number represents the numerical value of the parameter you want to communicate. This value can be exact but is usually accompanied by an uncertainty. It is important to distinguish between the calculated value and the uncertainty. When presenting results, the value of the parameter that will be communicated is usually rounded off to an appropriate number of significant figures to indicate an uncertainty in the number. A common rule for rounding figures is that the last significant figure should be of the same order of magnitude as the uncertainty. However, this also implies that there is some knowledge about the size of the uncertainty. In complex systems like an LCA model, the information of uncertainties in the calculations is usually rather poor. The rounding process can then be quite random and, in order not to give an impression of too accurate data in the models, it is often decided to round off strongly when presenting the final results. In this way, the values of the parameters are mixed with their uncertainties, in a sometimes undesirable manner.

When a number is rounded off, a rounding error occurs (Berendsen 2011). If the rounding is strong, a significant rounding error can be achieved. Rounding errors can also accumulate in large calculations. Due to these reasons it is recommended to only round off the final results that are communicated and not intermediate calculations. Rounding of the final results can however lead to problems in the development of large LCA models with many input datasets, since the numbers then are assigned with rounded figures. To reduce the rounding errors in LCA models, it should be recommended to also communicate, transfer and use data that are not rounded off but the pure calculated figures from the models. For analysis and increased readability, rounded off values with an appropriate number of significant figures should still be used and presented.

Table 1 Mathematical rules for uncertainty propagation calculations.

Application	Rules for error calculations applicable to Average deviation	Rules for error calculation applicable to Standard deviation	Comments
Addition and subtraction: **(z±Δz)=(x±Δx)+(y±Δy) or (z±Δz)=(x±Δx)–(y±Δy)**	$\Delta z=\lvert\Delta x\rvert+\lvert\Delta y\rvert$	$\Delta z=\sqrt{(\Delta x)^2+(\Delta y)^2}$	For both addition and subtraction
Multiplication by a constant **(z±Δz)= a*(x±Δx)**	$\Delta z=a*\Delta x$	$\Delta z=a*\Delta x$	Multiply the uncertainties with the constant
Multiplication and division **(z±Δz)=(x±Δx)*(y±Δy) or (z±Δz)=(x±Δx)/(y±Δy)**	$\frac{\Delta z}{z}=\frac{\Delta x}{x}+\frac{\Delta y}{y}$	$\frac{\Delta z}{z}=\sqrt{\left(\frac{\Delta x}{x}\right)^2+\left(\frac{\Delta y}{y}\right)^2}$	Use relative errors and add all relative errors to calculate the resulting relative error
Products of powers **$(z\pm\Delta z)=(x\pm\Delta x)^m*(y\pm\Delta y)^n$**	$\frac{\Delta z}{z}=\lvert m\rvert\frac{\Delta x}{x}+\lvert n\rvert\frac{\Delta y}{y}$	$\frac{\Delta z}{z}=\sqrt{\left(\frac{m\Delta x}{x}\right)^2+\left(\frac{n\Delta y}{y}\right)^2}$	
General for R=f(x, y, z…)	$\Delta R=\left\lvert\frac{\partial f}{\partial x}\right\rvert\Delta x+\left\lvert\frac{\partial f}{\partial y}\right\rvert\Delta y+\left\lvert\frac{\partial f}{\partial z}\right\rvert\Delta z+\cdots$	$\Delta R^2=\left(\frac{\partial f}{\partial x}\right)^2\Delta x^2+\left(\frac{\partial f}{\partial y}\right)^2\Delta y^2+\left(\frac{\partial f}{\partial z}\right)^2\Delta z^2+\cdots$	Use dx=Δx as the error in x… etc. for dy, dz… Use average value of x, y, z…to calculate the numerical value of the partial derivatives.

5 State of art – Uncertainty incorporation in LCA

5.1 Methodological state of the art

Attempts to include uncertainties and variations in Life Cycle Assessment have been numerous during the past decades. The importance and impact of the uncertainties on the results and validity of the assessment have contributed to the increased research focus this topic has received during this period. LCA has, as have been mentioned before, been utilized in many different areas and industries where the environmental impact is significant. The topics for the LCA are therefore widespread between many differing areas, even though the inclusion of uncertainties is a common denominator. Here follows a brief description of a number of such attempts with a short analysis of the method used and its usefulness.

One of the first attempts of considering uncertainty in LCA was presented by Huijbregts (1998a, 1998b) who described ideas for a framework that included a categorisation of uncertainties. Here, uncertainties were divided into 6 categories: 1) parameter uncertainty; 2) model uncertainty; 3) uncertainty due to choices; 4) temporal variability; 5) spatial variability; 6) variability between sources, where the categories can be seen as sub-categories to aleatoric or epistemic uncertainties.

The uncertainty due to choices considers uncertainties induced in LCA due to subjective choices that are needed concerning e.g. weighting of different greenhouse gases, and can be reduced by standardizing the LCA procedure. Temporal variability considers the difficulties in including time-dependent variations in e.g. factories and other production, where emissions may vary during and between individual days while it is common to use yearly average in LCA. Spatial variability is related to differences in environment, e.g. emissions for different geographic locations. Uncertainty due to variability between different sources is very important for manufacturers, if a generic emission value is used instead of factory specific, the result from the LCA may be either beneficial or unfavourable depending on the emissions at the actual factory.

In the second part (Huijbregts 1998b), a case study was presented where parameter uncertainty and uncertainty due to choices were included through the use of stochastic modelling. A limitation was the possibility to use this modelling for a large number of parameters due to computational capacity. A solution for this was suggested, in which a broad sensitivity analysis is performed initially with a full stochastic modelling only including key parameters. The lack of accurate data was also pointed out as a limiting factor for obtaining results that can be used in comparisons.

Björklund (2002) chose to include even more categories apart from those described by Huijbregts (1998a, 1998b) and also divide the parameter uncertainty into sub-categories, with the new categories: 1) data inaccuracy; 2) data gaps; 3) unrepresentative data; 4) epistemological uncertainty; 5) mistakes; 6) estimation of uncertainty. The first three relate to the parameter uncertainty, while the other new categories are related to difficulties and deficiencies in understanding the studied system and LCA-method. Although, the above categorisation is useful, it contains subjective elements and might not be fully consistent.

Björklund (2002) also presented a review of possible methods for sensitivity analysis and uncertainty analysis that can be utilised within LCA. A common factor for using the different methods is the lack of data, thus limiting several methods severely. It is also pointed out that the usefulness of including uncertainties in LCA is not only the quantitative numbers, but also that it gives an opportunity to improve the solution or system used. Even though the numbers can’t be verified completely, to find sensitive parameters and indicative uncertainties may influence the results positively and contribute to better environmental impact since they will increase the understanding of the role of uncertainties.

Another review of uncertainties in LCA and possible methods for quantification was presented by Baker and Lepech (2009). They point out that since LCA is a flexible tool that can be applied for many different fields, it is difficult to develop a general method for incorporating uncertainty. It can be more valuable to characterise uncertainties in a specific field, as in our case with infrastructure, and for different stages of a process.

Hoxha et al. (2017) studied the effect of uncertainties in input parameters for an LCA by focusing on variations in building materials for 30 building projects in France. As input, values from the EPD-system (EPD 2015) were obtained with the output focused on non-renewable energy, waste and global warming potential. To incorporate uncertainties, an analytical method based on Taylor series expansion and Analysis of Variance (ANOVA) was used. With this method, uncertainties can be included by mean and variance of the parameter and the relative contribution to the environmental and uncertainty impact for each parameter can be calculated. A more detailed description can be found in the paper. The input values were obtained from either database values or in discussion with experts, which may limit the validity of the output values.

The results in this study showed that the variability and uncertainties for the building materials used as input have a large impact on the possibility to compare different alternatives. The difference in GWP have to be larger than 15-20 % to be able to say that one alternative is better than another, due to the variability in the results. This indicates that comparisons between different buildings can be made, but the difference has to be significant, which may be problematic when choosing between options for a single project.

Geisler et al. (2005) assessed uncertainty in LCA using generic uncertainty factors for situations where no specific data exists. The studied case was two plant-protection products using Monte Carlo simulation for propagating parameter uncertainty. The parameters were all assumed to be lognormal distributed, which often is the case in studies where values below zero is unrealistic. No significant differences were found in the comparison between the results, which the authors suggested was due to a large uncertainty in the impact scores. The uncertainty was about 40 % for GWP, making this a bit larger than what has been found in other studies. The study points out the importance of considering the real variation in input parameters, since it was difficult to find any possible generic uncertainty factors. Small differences between products will then provide small differences in impact, while model uncertainties and uncertainties due to choices are better to treat by transparent regulations.

Another method for handling uncertainties in LCA was proposed by Olivetti et al. (2013) with the aim of reducing the time of a probabilistic analysis. They used so-called probabilistic under-specification for assessing the uncertainty of each parameter. Depending on how much information that was available and what type of result is needed, distributions can be assigned at different specified levels. A combined distribution can be used for lower levels with less specified input parameters, which then may reduce computational time. A Monte Carlo simulation is the basis of this analysis as well; this further confirms the usefulness of this method. The same method has also been used by Tecchio (2015) and was originally developed by Patanavanich (2009).

Bisinella et al. (2016) did not assess the uncertainty in LCA as much as they assessed the sensitivity of the parameters to find a method for observing the most influential. An analytical formulation was used and compared with Monte Carlo simulations, to establish whether the method could correctly predict the most influential parameters. The analytical method was based on Global Sensitivity Analysis (GSA) and error propagation theory, and thus derived from already established methods. The results showed that this method gives similar values for the final variance of the LCA results as for the Monte Carlo simulation, which makes it useful for finding influential parameters. It can’t be used to find any differences between two different LCAs however, since it does only provide variation. The usefulness of the method is then limited for situations where comparisons are necessary or where a Monte Carlo simulation may be performed within reasonable time limits.

A similar study was performed by Lacirignola et al. (2017) where global sensitivity analysis was used to identify key parameters in a LCA case. The basic idea is to use GSA to perform an analysis where the variances of the individual parameters are related to the variance of the output. By this, it is possible to see how large influence each parameter has on the result. A drawback with this method is that you need the distributions and its parameters; if you have this it can be just as good to perform stochastic modelling. The results of GSA are heavily influenced by the initial assumptions; this was also concluded in the study.

The global sensitivity analysis was also used by Cucurachi et al. (2016) to more systematically find the most important parameters in an LCA including uncertainties. The case used has limited value when compared to infrastructure LCA due to few parameters, which makes any conclusion on the methods suitability difficult. Their aim was to find some common ground for GSA in LCA, but they conclude there is still a lack of common ground due to limited studies using this methodology.

Zhang et al. (2016) used a Monte Carlo simulation to estimate uncertainty propagation for a LCA of a bridge in China. Another part of the study was to assess different distribution types and their validity for the analysis. The results showed that a normal distribution was best suited for most parameters due to the uncertainty of the estimation. It was also found that for energy consumption, the variability in the results for the case study was quite low, only 6 %. For other impacts such as human health the variation was much larger, up to 40 %. This shows that the desired output may govern the level of uncertainty significantly and that the system boundaries are of great importance.

Batouli et al. (2017) attempted to compare different types of pavements by the use of LCA incorporating uncertainties via a Monte Carlo simulation. The variation was based on an assumption of a coefficient of variation of 10 % for all input variables, thus leading to a distribution for the final outcome. The results showed that even with a crude uncertainty assumption such as this, it is possible to distinguish between two different solutions. It was also shown that the pavement with lowest impact in the construction phase gave an enormous impact due to future maintenance, emphasizing the importance of the system boundaries in the LCA.

Another study on LCA for pavements was performed by Yu et al. (2017) where the problem of using data from different sources was addressed. They used Monte Carlo simulation with data adapted with a weighting system to compare environmental impact for bitumen. To include variation in data quality, the approach from Ecoinvent with a data quality pedigree matrix was adopted (see chapter 5.3.1 for a description of this Ecoinvent approach). A distribution was assigned to each parameter based on the data quality index, with a difference in type of distribution based on this index. The weighting was performed to make certain that data with higher quality was given a larger influence over the final results, even though it provided less variation. From the study it was concluded that the method can be used for determine how good an estimate is and if differences between products are significant. The data quality was also here the most important factor for getting a usable result from the LCA, but the methodology used can be valuable in some cases.

Mackenzie et al. (2014) accounted for uncertainties when comparing the environmental impact from two different pig farming systems in different regions in Canada. They used a combination of specific measured data and input data from Ecoinvent database with distributions based on the most suitable form, normal, lognormal or triangle distribution. A Monte Carlo simulation with 1000 repetitions was performed, giving results for 5 different impact categories including GWP.

The results showed no significant difference between the two systems, despite a significant difference in several input parameters. They found however that it is possible to efficiently use Monte Carlo simulation to incorporate uncertainties when suitable distributions are available.

Another area in which LCA has been frequently used is in waste management. Clavreul et al. (2012) attempted to quantify uncertainties in such systems using different methods. A case study was set up to compare the different methods for uncertainty analysis with input values from a waste management database. The methods in question were three forms of sensitivity analysis, scenario analysis, uncertainty propagation and uncertainty contribution. The results of the analysis led to a proposal for a framework where different steps can be taken depending on what kind of result that is needed, see Figure 2Figure 2 A sequential approach for quantitative uncertainty analysis. (Clavreul et al. 2012). This procedure could be useful for other interest areas than waste management, although the same problems with lack of input data are present for this area as well.

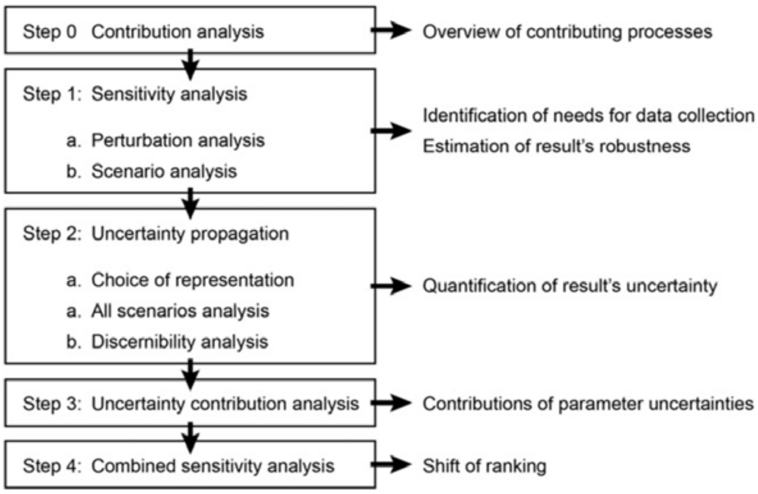

Figure 2 A sequential approach for quantitative uncertainty analysis. (Clavreul et al. 2012)

One interesting study comparing different LCA methods and cases for buildings was presented by Säynäjoki et al. (2017). In the study, a review of LCA studies found in literature was made with the focus of comparing the results and see if it could be possible to use LCA for producing policy guidelines at the current state of the art. 116 cases were analysed, with three different types of LCA methodology found in these cases; process LCA, input-output LCA and hybrid LCA, using differing ways of defining the LCA. The variations in results in the studied cases were large, the total amount of CO_2/m^2 gross area varied from 0.03 to 2.0 tonne, see Figure 3. A difference deemed much too high for any comparative analysis to be possible between the different cases. The reasons for the large variation were difficult to assess, but the largest factor was the choice of LCA method. Still, the differences using the same method were large, thus showing that input data and especially the choices made by the user have a large influence on the results. The authors suggested, in line with the thinking in this report, that since LCA will give different results depending on the method, program and person, transparency is at the present time the most important factor for being able to use LCA results in a reliable way. Otherwise, it is possible to show policy makers results that seem acceptable, when they in reality can’t be used in comparison with other results.

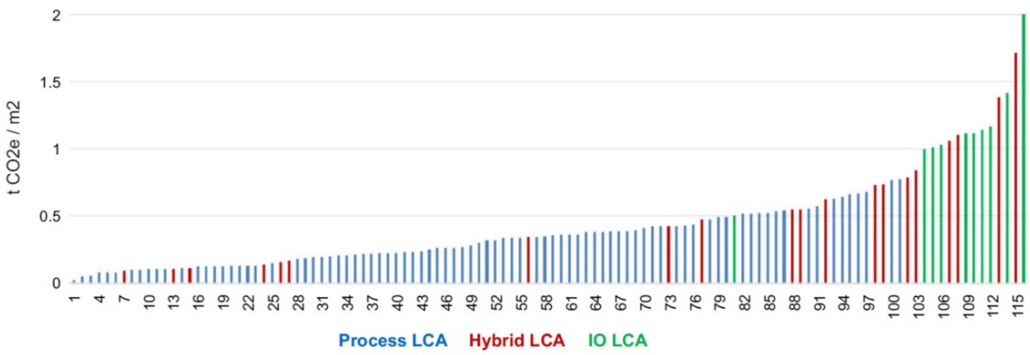

Figure 3 GHG emissions per gross m^2 of the reviewed case studies (Säynäjoki et al. 2017).

One extensive survey of different methods that may be used for analysis of uncertainty propagation in LCA was performed and presented by Groen et al. (2014). To demonstrate the usefulness of the different methods, three case studies of varying complexity were shown with the same coefficient of variation in each input parameter. The tested methods were full Monte Carlo simulation, Latin Hypercube sampling, Quasi Monte Carlo sampling, Analytical uncertainty propagation and fuzzy interval arithmetic. For an explanation in detail of the different methods, we refer to Groen et al. (2014), since it is not relevant to include them here.

According to their results, the most efficient methods concerning computational time and accuracy were Latin hypercube sampling and Quasi Monte Carlo sampling. The two fastest methods were the analytical and fuzzy interval, however, they did not give sufficiently accurate results. Full Monte Carlo simulation provided good results but was time consuming in comparison with the other methods, but the differences are small. The study shows that the method chosen is not the most influential factor for uncertainty analysis, but that it is important to use it in a consistent manner.

The study by Groens et al. (2014) was mostly based on findings from Lloyd and Ries (2007) who performed a survey of approaches for analysing uncertainty in LCA. The survey covered 24 LCA studies, which included uncertainty analysis, studying which methods that were commonly used and trying to review their suitability for enabling better decisions. The most common method for incorporating uncertainty was some kind of stochastic modelling, which is in line with the other findings in this report. Most used was the Monte Carlo simulation with distributions for the input parameters, where the data were estimates from either databases or as generic values. They also found that in different studies, the opinion on which is the most suitable method varies. Some authors suggest that stochastic modelling cannot be used, however, since there is a lack of data while others specify that it is impossible to use anything else due to the size of the analysed system.

An interesting aspect found by Lloyd and Ries (2007) is that only 33 % of the analyses included model uncertainties in the calculations. Since the model uncertainties have a very large impact on the results, this is surprising. They could not find a common reason for excluding this in the studies, but it shows that even if parametric uncertainties are included, the result might not be reliable. They also conclude that even though uncertainties exist in LCA, it is possible to use quantitative uncertainty analysis to improve decision making by giving estimates on the likelihood that one alternative will have lower impact than another using stochastic modelling.

Basson and Petrie (2007) suggest that uncertainties affecting the outcome of the result and uncertainties that hinder valuation between different results can be separated and treated differently. They developed an approach for considering uncertainties as described, using Monte carlo simulation, for estimating uncertainties from the input parameters, as they labelled “technical uncertainties”. The uncertainties related to valuation of different results, “valuation uncertainties”, were treated with a multiple criteria evaluation methods and sensitivity analysis.

To test their method, a case study was performed on a power plant with two different solutions for upgrading the capacity. In the study, the Monte Carlo simulation was first used to estimate performance scores for the two solutions for different categories such as various environmental impacts and financial cost. The comparison was then performed using value functions where the worst and best values for each solution were used as range. To obtain these functions, it is also imperative to use some kind of weighting function considering typical values that decision makers would be willing to accept for each category. The design scenarios could then be compared for the two solutions using this approach. In this particular case, the value functions overlapped due to the uncertainties involved, which was expected. It was however possible to see that one solution tended to be better than the other. By providing more information on the solutions and not only showing one value for each, the complexity of the decision is however shown and a better basis for this decision is given.

Lasvaux et al. (2015) made a comparison on how LCA is affected by the use of different input data. Product specific data was used in comparison with generic data from databases to find out how large influence this can have on the results. No specific method for including uncertainty was used, the study points however out the importance of data quality. For the comparison, the data was obtained from either Ecoinvent database (Ecoinvent 2015) or the EPD-system where product specific data was obtained. For GWP, the difference was as large as 26 % depending on the type of data, while for other indicators the difference was even larger. It shows the importance of the data quality, but also the possibility for improvement in the manufacturing industry. If product specific data can be used, it gives an incentive for improving the environmental footprint for a product.

Gou and Murphy (2012) performed a case study on biopolymers to investigate the effect of the time horizon of the results of an LCA, from 20 years of use to infinity. They used Monte Carlo simulation for incorporating uncertainties, with different tests to see the reliability of the results. The data was obtained from literature or databases using the pedigree matrix approach for the uncertainties. The results showed that the time horizon can have a large influence on the results, which was somewhat expected. This confirms the thinking in the building industry that the whole service life has to be included when estimating environmental impact, and not just manufacturing or short time periods.

Liu et al. (2013) compared uncertainty analysis using Monte Carlo simulation with fuzzy set theory for LCA of a factory in Taiwan. The methods were only compared from a theoretical point; it is difficult to draw any conclusions on the usefulness based on their findings. It is pointed out however, that fuzzy set theory using probabilistic distributions will significantly reduce the number of simulations needed.

A slightly different approach with stochastic modelling was presented by Lo et al. (2005), where Monte Carlo simulation was combined with Bayesian inference. This was suggested as a possibility for better considering simulations where lack of data is a problem. The Bayesian inference was used to update the input for the Monte Carlo simulation using newly observed data. The use of this methodology is limited, since newly observed data could be inserted directly into the simulation with similar impacts on the results.

Røyne (2016) studied the effect of system boundaries on uncertainties in the result of LCA for forest products. As expected, the inclusion of different phases such as usage and manufacturing of a product have a large impact on the results. Also, the total number of activities included has a large influence, where the result depends on were in the supply chain the boundaries are set.

An alternative method for including uncertainties could be the use of reliability theory. This has been used successfully in various applications such as structural engineering, chemical engineering and manufacturing industry for decades. The general idea is to reduce the number of calculations needed compared with Monte Carlo simulation by the use of a limit state, which specifies a certain condition. The probability of meeting this condition can then be calculated with reliability analysis methods, see e.g. Stewart and Melchers (1997) or Nowak and Collins (2000) for a detailed description of the actual reliability calculation methods.

The possibility of using reliability theory in LCA has been studied by Wei et al. (2016). The main aim of their study was to use reliability analysis as a tool for comparing different LCA results for two insulation systems and by this give support for decisions concerning environmental impact. The method is based on a limit state equation saying that insulation A is better than insulation B, and the probability of this statement being true is calculated. In the study, the number of influencing parameters is limited to 5 for each insulation. A full Monte Carlo simulation is also performed, which enables a comparison between the two methods. Their conclusion is that reliability analysis can be used efficiently for this kind of comparison and that the time is less for this calculation compared to Monte Carlo simulation.

To be able to use reliability analysis with LCA would be a powerful tool, since it enables comparisons between different solutions and products. There are however problems with using this type of analysis, one of them being limitations in data availability. For reliability analysis, we need to know the distribution type, mean value and standard deviation just as for other methods. Another major drawback is the number of parameters in the analysis. In reliability methods in engineering, we do not have that many parameters, which may cause problems in a LCA with several thousand input parameters since the methods may be difficult to apply.

Another challenge could be the definition of the required limit state function. In reliability analysis, the limit state function describes the goal we have as limit, e.g. in structural engineering it can be failure of a structural member, and we calculate then probability of exceeding that limit state. This limit state can be difficult to define for LCA, as it is not clear what we want to achieve with this limit. A poorly defined limit state may give results that are unreliable and hard to interpret.

5.2 Overview summary of methodology

The previous section shows that many studies exist on how to treat uncertainties in LCA. There are many possible methods for including uncertainties in a LCA-tool, the difficulty is to find a method that is not too complex but still provide reasonable results. A summary of the analysis methods used for uncertainty analysis in the studied papers and reports is shown in Table 2. Here, it can be seen that stochastic modelling using Monte Carlo simulation is the most common method found in literature. Other methods exist, which may reduce computing time, a factor that may limit the use of Monte Carlo simulation. Several methods have only been used for a small number of parameters; this may be a limiting factor since many LCA have a very large number of input values. A major challenge is perhaps not computation of the total uncertainty itself, but the quantification of the uncertainties in the input parameters, especially if it requires the description of the probability distribution functions.

Table 2 Summary of used uncertainty analysis methods.

Author	Uncertainty analysis					Sensitivity analysis
	Monte Carlo sampling	Latin hypercube sampling	Analytical method	Reliability analysis	Fuzzy set theory	Global sensitivity analysis
Mackenzie et al. (2014)	x					
Hoxha et al. (2017)			x			
Geisler et al. (2005)	x					
Olivetti et al. (2013)	x					
Patanavanich (2009)	x					
Tecchio (2015)	x					
Bisinella et al. (2016)	x					x
Lacirignola et al. (2017)						x
Cucurachi et al. (2016)						x
Zhang et al. (2016)	x					
Batouli et al. (2017)	x					
Yu et al. (2017)	x					
Clavreul et al. (2012)	x					
Groen et al. (2014)	x	x	x		x	
Basson and Petrie (2007)	x					
Gou and Murphy (2012)	x					
Liu et al. (2013)	x				x	
Lo et al. (2005)	x					
Wei et al. (2016)				x		
Heijungs et al. (2014)	x		x			

Many authors point out the importance on input data and the lack of appropriate values. Attempts have been made to consider this generically by the use of standard values for distribution parameters. This can be valuable if the aim is to show the effect of uncertainties, but may not improve the actual level of uncertainty for the results. In a worst case scenario, this may even contribute to results that give fewer incentives for improving a product or process since the impact of this may not give better results due to other uncertainties being more influential. A more simple method using sensitivity analysis may therefore be more appropriate for showing improvements for specific processes or products. In chapter 7 of this report, both full probabilistic and a more simple analysis using sensitivity factors are demonstrated in a case study to show to possibilities for each type of method.

5.3 Data quality

The data quality has, from the beginning of the LCA applications, been identified as a very important aspect and a base for reliable LCA results. In the ISO 14044 standard, which regulates the performance of LCA, methods to ensure data quality have been included. The methods are more of a supervisory and controlling nature than quantitative in order to calculate the uncertainties in input and final results. The aim of the methods is more to check the reliability of the data used and define its background, source, quality and application. The data sources can be very different from theoretically calculated data from literature to measurement data from one or several production units. In the ISO standard, the quality is described in a specified way. Information about the data sets used should address the following; time-related coverage, geographical coverage, technology coverage, precision (e.g. variance), completeness, representativeness, consistency, reproducibility, sources of the data, and uncertainty of the information. The extent of the information can vary significantly and such data can also be difficult to obtain. Other important information is layout of the LCA models and strategic choices such as allocation and handling of avoided processes in system expansion.

One of the most common systems to regulate LCA calculations is the Environmental Product Declaration system (EPD 2015) based on ISO 14025:2006 Type III. The aim of the EPD system is to standardize how an LCA shall be performed for e.g. a specific product group. Specific rules called Product Category Rules (PCR) are developed for each product category in order to equalize the calculation and in that way reduce the unwanted variations, especially for the comparison of the environmental performance for the products. Many different aspects are regulated, which are specific for the product group. The EPDs contain the LCA results and are published at the EPD-system's web site (www.environdec.com). To verify that there is no bias in the delivered data, or intentional fraud designed to have a better-looking product, a verification system based on independent verifiers exist in the EPD-system. In the EPDs, where the LCA results are published, no uncertainty data is available. The reason for this is that it has been very difficult to obtain such data and hardly any LCA study includes such information. It would thus be desirable if any kind of uncertainty assessment could be included but this requires developed methods and standards for such implementation. There is an overconfidence in the efficiency of regulations and their ability to reduce uncertainty, since many factors that affect the results such as model uncertainties and uncertainties due to choices are very difficult to reduce with regulations of the input parameters.

Another regulation system for collecting data and performing LCA was developed by the EU, called the ILCD-handbook (ILCD 2010a, ILCD 2010b). This handbook consists of several documents, regulating what kind of information is needed and how data should be collected. It also provides guidelines for how the actual impact analysis should be performed. To assess data quality, there is a rating system where different aspects of the data can be rated according to some subjective categories. After this rating, the different rating categories are combined into a final data quality rating for the data set. The five criteria listed are overall data quality, method for LCI, nomenclature, review and documentation.

The main issue with this type of data quality system is that it is difficult to capture effects of uncertainties useful in LCA-calculations. It is efficient enough to use for estimating how good an individual result is in relation to the mentioned categories and the related rating grades, but it is difficult to assess how good a result is in relation to other LCA-calculations using other data. Since the data quality review is subjective, the review should be made by the same independent expert for all data sets. This is not realistic due to the amount of time needed for such a task, which means that different data sets are still difficult to compare. To study the effect of data quality and impact of uncertainty and variations, another approach is needed.

5.3.1 Ecoinvent

The Ecoinvent database aims to standardise data for LCI covering many different activities, a detailed description can be found in Weidema et al. (2013). The data found here are intended to be used as background data for processes and activities where project specific data are hard to find. The database consists of data that have been obtained during many years and from a large number of sources. It is possible for e.g. a manufacturer to supply their data to Ecoinvent, thus providing the database with up to date values and ensuring that their product has the correct environmental impact.

When using data from Ecoinvent, it is important to consider the uncertainties that arise though the use of such values. In the data quality guideline (Weidema et al. 2013), a procedure for estimating the uncertainty and variation in a parameter is described. The procedure consists of different steps depending on the type of values for a specific dataset. If it is a large sample, the distribution and standard deviation can be calculated directly. For a small sample, an approximate standard deviation can be calculated, which is related to the range of the given data set.

For the common situation where only one source of information exists with only one specific value, the procedure suggests that a lognormal distribution is used and that the standard deviation is calculated based on the type of parameter and quality of the data. A default basic uncertainty is given based on the general uncertainty in a parameter. As an example, the database specifies a larger variation for CO emissions than for CO_2 emissions, since they show a larger uncertainty in calculations. These factors are based on expert judgment, and are thus not real validated values.

An additional uncertainty is added to the basic uncertainty based on data quality indicators. A matrix approach is used, see Table 3 (Weidema 2003). The quality of the data is assessed by five indicators; reliability, completeness, time of collection, geographical correlation and technological correlation. The additional variance that should be added to the basic variance can then be obtained depending on how the data is placed in these five categories.

The approach for assigning uncertainty to parameters described in Ecoinvent is useful for getting a data interval, but it still requires the user to assess the data and it is a crude method for obtaining such specific numbers. Since the purpose of including uncertainties is to get more reliable results, there is a risk that if subjective values are used, it may still give subjective results giving a false sense of more accuracy. It does not consider model uncertainty, which may be the most crucial part of the analysis.

Table 3. Pedigree matrix used to assess the quality of data sources (Weidema 2003)

Indicator score	**1**	**2**	**3**	**4**	**5** (default)
Reliability	Verified[5] data based on measurements[6]	Verified data partly based on assumptions ***or*** non-verified data based on measure- ments	Non-verified data part- ly based on qualified estimates	Qualified estimate (e.g. by industrial ex- pert)	Non-qualified estimate
Completeness	Representative data from all sites relevant for the market consid- ered, over an ade- quate period to even out normal fluctuations	Representative data from >50% of the sites relevant for the market considered, over an adequate period to even out normal fluc- tuations	Representative data from only some sites (<<50%) relevant for the market considered ***or*** >50% of sites but from shorter periods	Representative data from only one site rel- evant for the market considered ***or*** some sites but from shorter periods	Representativene ss unknown or data from a small number of sites ***and*** from shorter periods
Temporal cor- relation	Less than 3 years of difference to the time period of the dataset	Less than 6 years of difference to the time period of the dataset	Less than 10 years of difference to the time period of the dataset	Less than 15 years of difference to the time period of the dataset	Age of data unknown or more than 15 years of difference to the time period of the dataset
Geographical correlation	Data from area under study	Average data from larger area in which the area under study is included	Data from area with similar production conditions	Data from area with slightly similar produc- tion conditions	Data from unknown ***or*** distinctly different area (North America in- stead of Middle East, OECD-Europe instead of Russia)
Further tech- nological cor- relation	Data from enterprises, processes and mate- rials under study	Data from processes and materials under study (i.e. identical technology) but from different enterprises	Data from processes and materials under study but from different technology	Data on related processes or materials	Data on related processes on laboratory scale ***or*** from different technology

6 Methodological aspects for uncertainty evaluation

6.1 General aspects

Most data and especially LCA data sets contain variations, an aspect that needs to be handled for any type of input parameter. Some kind of average value is often used to describe these variating values in one number. The uncertainty is the component that characterizes the variability of the estimated values. Thus, the uncertainty needs to include all the different types and sources of variations. As has been stated before, there are many different types and sources of variations for LCA calculations and models. The handling of these variations in calculations results in different uncertainties for the data, it is therefore important to carefully study these variations with their different origins and content. Some may be handled with uncertainty analysis methods, while others are more difficult to incorporate or may even have to be excluded such as intentional errors, mistakes or misunderstanding of a process. In the three following lists below, examples of different variations that are related to LCA is given. The three lists also include an example of categorisation of the variations into; model variations, variations in input data and variations due to mistakes or intentional errors.

Variations/Uncertainties related to the LCA model used and the boundary conditions chosen for the calculations:

- System boundaries, not covering all relevant processes or parameters.
- Wrong boundaries, only part of the process is included e.g. construction phase but not user phase if this is wanted.
- Simplifications of the system and cut-off criteria, processes not calculated from the source and to end-of-life.
- Choice of methods and other technical information, e.g. choice of end-of-life, recycling, closed or open loop, system expansion and avoided processes.
- Allocation assumptions and methods.
- Choice of functional unit. Is the functional unit actually completely equal for all aspects in a comparison?
- Choice of characterization factors.
- Choice of what to analyse in the study.
- Interpretation of the results.
- Normalization of the results (weighting, assessment of environmental impacts).

Variations/Uncertainties related to the input data in the model and where this data is obtained:

- General data quality (specific LCA data from an object or general database data).
- Wrong input data.
- Physical variation in a parameter e.g. variations in raw materials, fuel, weather conditions etc.
- Statistical variation in a parameter.
- Measurement uncertainties of parameter data.
- Rounding errors in input data obtained from other LCA-results.
- Different manufacturing processes.
- Different design of a product with the same function e.g. different bridge constructions.

- Age, operation and maintenance aspects of the studied object.
- Geographical placement of project site.
- Future or existing infrastructure i.e. is the object already built so data can be available.
- Is it one specific infrastructure object or the mean of several objects.
- Assumed service life for construction products and processes.
- Time relevance, when was the data collected.

Variations/Uncertainties related to actual mistakes or misunderstanding of LCA concepts. Related to the other categories:

- Intentional errors – fraud.
- Calculation errors – random mistakes.
- Calculation errors – wrong assumptions, lack of knowledge.
- Misconceptions when collecting data or choosing the appropriate model.

As shown in the lists, these uncertainties will cover many different aspects and levels of the uncertainty analysis. It is also apparent from the examples that uncertainties consist of many different components, which together give a total uncertainty. The effect of the various uncertainties can also be very different. For example, the impact of choosing different boundaries for the analysis may give a much larger impact on the results than a physical variation in one parameter. It is therefore important, in the discussion of the effects of uncertainties, to regard the actual influence. A very important aspect when dealing with uncertainties in LCA is thus to take into account the variations of all the different components. In this way one can assess the different variations and also include or exclude different components. The situation is of course different when developing a new LCA dataset than trying to assess the uncertainties of an unknown but existing LCA dataset. In a new LCA dataset, it is thus possible to control which variations are to be included in the calculations. For example, for a dumper transport in a construction site, the diesel consumption can vary significantly due to several reasons such as hilly terrain conditions, if it's rainy and muddy, the driver's skill etc. The question then is which of these variations are appropriate to include in the dataset and if data is available for the different variations. In this way, the uncertainty can be controlled to some extent. This way of thinking can be applied especially when the dataset will be used for comparison, for example, in an Environmental Product Declaration (EPD) and can then be a part of the Product Category Rules (PCR). To include variation that will include rain condition, as in the dumper example above, can be directly misleading and increase the uncertainty in the comparison of the EPDs.

In the lists above, an attempt to categorize the different types of variations has been made. As can be seen, many of the listed sources of uncertainty can fall into more than one category. In the literature on uncertainties there are different ways to categorize the different types of uncertainties. The following list gives an example that is more comprehensive than in our example above. (Kennedy et al., 2001, Wikipedia).

Parameter uncertainty: Uncertainties emanating from input parameters whose exact values are unknown and cannot be obtained.

Parametric variability: Uncertainties emanating from the variability of input variables of the model.

Structural uncertainty: Uncertainties emanating from the deviation between the structure of the mathematical model and reality.

Algorithmic uncertainty: Uncertainties emanating from approximations in mathematical calculations e.g. incomplete algorithm, numerical solved equations, rounding errors etc.

Experimental uncertainty: Uncertainties emanating from the variability of experimental measurements, also known as observation errors.

Interpolation uncertainty: Uncertainties emanating from data that are obtained by interpolation or extrapolation in the absence of actual data.

Another way of categorising could be to just use the basic levels of aleatoric and epistemic uncertainties described in chapter 4. This will be further explored in the next section of this chapter. This type of categorisation can make it easier to check, handle and control the variations in a systematic way. To exclude or include different variations in an LCA dataset affect not only the uncertainty of the dataset but also the actual underlying variations in the dataset. This decision is always difficult to do because it will affect the entire dataset but is a very important aspect. The decision can be made by the practitioner of the LCA but it can also be standardised.

Thus, based on the categories described, it is possible to assess which uncertainties that should be included in an LCA model and which uncertainties that are more appropriate to handle through legislation and standardisation. Effects due to uncertainties related to parameters, model, spatial and temporal variabilities and variability between sources are suitable to analyse with probabilistic methods, while other categories such as uncertainties due to mistakes and lack of understanding of the system or method, or intentional errors are difficult to include in such an analysis and are therefore normally not included. As a comparison to this, it can also be mentioned that when collecting LCA data for a process, neither, for example, data for accidents are included, but the process is described under normal operating conditions. This should also be taken into account in an uncertainty analysis.

6.2 Aleatoric or epistemic uncertainties in probabilistic model validation – proposed methodology

LCA models are usually very complex mathematical models with a lot of various input data. As already has been shown, the input data comes with an uncertainty. There are also deviations between the model and the reality and sometimes, the reality (the real process) is not constant either. This will of course lead to uncertainties in the results from the model. Concerning the available information, there is also a difference between a process where you have access to primary data for the process and an unknown process where you only have an LCA dataset for the process (usually without any information about uncertainties). This is thus the situation that needs to be handled. The question here is how to deal with the uncertainty in such a situation.

As shown before, it can be a good start to take a closer look at the different types of variations that lead to the uncertainties. Which are the most fundamental uncertainties and which can be excluded or avoided? For this purpose, a new categorisation can be introduced based on the general definitions of uncertainty found in chapter 3. The new categories are only two - aleatoric (aleatory) uncertainties and epistemic uncertainties. These two categories are explained below:

Aleatoric (aleatory) uncertainty: Aleatoric uncertainty emanates from the natural randomness in a process. Thus, this uncertainty represents the variations that are unknown and cannot, in principal, be controlled by mathematical methods and more knowledge about the process. An example of such an uncertainty is the white noise from a measurement instrument or variability of material strength. This category usually also includes uncertainties that, in practice, are not possible to calculate even if a theoretic possibility can exist. This is thus a “true uncertainty” that cannot be eliminated or excluded. However, new knowledge can, in principal, transfer an aleatoric uncertainty into the next category that is the epistemic uncertainty.

Epistemic uncertainty: Epistemic uncertainty emanates from variations which are due to a lack of knowledge, and can be reduced and controlled by obtaining more information. Some of the epistemic uncertainties, however, are not calculated in practice because of different circumstances. Examples of this can be effects that are neglected in a process or effects of intentional simplifications of a model. This type of uncertainties could, in principle, be handled or eliminated in the construction process of the LCA data set.

As shown above, there is thus a possibility to divide the uncertainties into two basic groups – aleatoric and epistemic uncertainties. These are caused by many different variations in the model that needs to be sorted and handled, see Table 4. A good start is to calculate the total aleatoric uncertainty. This uncertainty represents the minimum uncertainty that can be achieved in the LCA model. The aleatoric uncertainties represents, for example, measurement uncertainty for a measuring instrument and these uncertainties cannot, in principle, be avoided or improved. This value represents thus the base for the uncertainty and should always be presented separately.

In addition to the aleatoric uncertainty, there are also epistemic uncertainties. This uncertainty is built up of different varying components, which, in principle, are possible to control by improved measurements, or include or exclude from the total variability. A developer of an LCA dataset can then determine, to some extent, the variations to be considered in the dataset and provide measurements of corresponding variations in the measured values. In this way, the uncertainties for a data set can be regulated. The uncertainties are thus not something given from the beginning, but something that can be affected.

In a case where you do not have access to basic process data and where you still need to assess the uncertainties, the situation is obviously more difficult. Even here, however, one could use the proposed strategy when approximating uncertainties. In some cases, LCA data builds on theoretical calculations of a process. In these cases, it may be easier to calculate the uncertainties as you have better control over what the process data contains than when actual measurement data is used since there is often a lack in background data for the measured values.

Table 4 A schematic example of an uncertainty calculation for an LCA.

Type of uncertainty	Type of variation
Epistemic uncertainties	Epistemic variation 1 Epistemic variation 2 Epistemic variation 3 … <u>Epistemic variation N</u> Σ total epistemic variability
Aleatoric uncertainties	Aleatoric variation 1 Aleatoric variation 2 Aleatoric variation 3 … <u>Aleatoric variation N</u> Σ total aleatoric variability
Total uncertainty	Total variability

However, basic variations in the process to be studied are suggested not to be included as variations but as different objects with different LCA models. Here, however, one must make an assessment of what is appropriate for the specific case. Regarding variations that may be caused by accidents, mistakes, ignorance or intentional errors, it is suggested that these are not included in a general uncertainty calculation. However, such analyses can of course be made for special purposes.

6.3 Methodology – illustrative example

To exemplify this methodology, the uncertainty in emissions from using a dumper truck is estimated using this procedure. The first step is to identify the aleatoric uncertainties relevant for this process, either by measurements performed by yourself or by a credited third party. Using Table 4 as reference, we obtain an uncertainty factor for the aleatoric uncertainty, which represents the minimum variation we can have. **Note that the values are only assumed examples used for illustrative purposes and no real measurements have been performed, these values should therefore never be used as reference for other studies!**

Since the purpose of this example is to illustrate how this methodology may be applied, the approach is kept simple by assuming that all variables are independent and that the uncertainty is represented with the variance of each variable, e.g. the square root of the standard deviation. For a real case, variances may not be available or relevant. In such a situation it may not be possible to use addition for the uncertainty values; rules of uncertainty calculation have to be followed (see chapter 3 and e.g. Berendsen 2011). The values are used for illustrative purposes only; other numbers will give differing results.

Table 5 Initial aleatoric uncertainties, estimations for a dumper truck. In the example, variance is used as uncertainty factor

Type of uncertainty	Type of variation	Uncertainty factor
Epistemic uncertainties	Epistemic variation 1 Epistemic variation 2 Epistemic variation 3 … Epistemic variation N Σ total epistemic variability	
Aleatoric uncertainties	Measurement noise, fuel (*l*) Meas. noise, engine (*l* to *km*) Statistical uncertainty Physical, fuel (fuel quality) Physical, engine (engine efficiency) Σ total aleatoric variability	0.005 0.01 0.01 0.02 0.05 0.095
Total uncertainty	Total variability	

In this example we have included uncertainties related to physical parameters, fuel and engine, used to power the dumper, measurement uncertainties related to the actual emission values and statistical uncertainties related to the number of measurements available.

The total aleatoric uncertainty for use in the LCA-calculation may then be obtained from this table. This procedure is similar to the current formats found in Ecoinvent and other sources where an uncertainty factor can be estimated using variances obtained from different sets of rules (Weidema et al 2013). If only aleatoric uncertainties were present, this number could be used in the calculations as input. In real situations however, the epistemic uncertainties will have an impact on the result. As previously stated, this influence has to be related to the actual purpose of the LCA in the specific case studied.

The second step of the procedure is to identify the possible epistemic uncertainties and assign numbers to these. Since such numbers are difficult to measure with measuring tools, they have to be found by expert judgment or interviews. In this example, the numbers are estimated by the authors. Using the same table for identifying the uncertainties we can obtain the following:

Table 6 Initial epistemic uncertainties, estimations for a dumper truck. In the example, variance is used as uncertainty factor.

Type of uncertainty	Type of variation	Uncertainty factor
Epistemic uncertainties	Driver variability	0.07
	Weather conditions	0.1
	Surrounding environment (terrain, topography)	0.05
	Tire conditions	0.05
	Maintenance of engine	0.03
	Maintenance of fuel tanks	0.03
	Seasonal variations	0.09
	Σ total epistemic variability	0.42
Aleatoric uncertainties	Σ total aleatoric variability	0.095
Total uncertainty	Total variability	0.515

As can be seen in Table 6, the epistemic uncertainties are assumed much larger than the aleatoric, which is in-line with previous descriptions in this report. This is due to the large variability than comes from the various sources included in this category. There is e.g. a very large variability depending on the weather conditions, since a lot more fuel will be consumed if the ground becomes muddy and slippery due to rain. These epistemic uncertainties are, according to the authors, the main reason for why uncertainty values and variations of up to 100 % are reported in other studies, since they can have a large influence.

When studying epistemic uncertainties in more detail, it can be seen that many of the included parameters may not be relevant in all LCA applications. If one wants to find an appropriate value for e.g. documentation, a large epistemic uncertainty including many different types of possible and perhaps peripheral variations, may not be relevant or even misleading. The same can be true if one wants to compare or improve emissions from dumpers, then the uncertainty related to e.g. weather, surrounding topography and tires might not be relevant. The actual relevant uncertainty and variability could therefore be much smaller than the value given in the table, since it depends on the use and purpose of the LCA. If it is included, the influence may be so large that other uncertainties are no longer of importance. The purpose of the LCA is therefore the most important factor governing the uncertainty level since it will influence which uncertainties that are of interest.

In a procurement situation, it is therefore important to be specific about the preconditions of the LCA. Epistemic uncertainties that affect all bidders may e.g. be excluded from the procurement process since they are not relevant for the outcome. Other factors, such as maintenance, could be controlled by regulations on suitable intervals, making the uncertainties possible to be reduced. For a case where e.g. the maintenance has been regulated, the external conditions have been removed and the driver variability is reduced, the uncertainties can be estimated to the values in the example below:

Table 7 Final uncertainty factor depending on application. In the example, variance is used as uncertainty factor.

Type of uncertainty	Type of variation	Uncertainty factor
Epistemic uncertainties	Driver variability	0.04
	Weather conditions	-
	Surrounding environment (terrain, topography)	-
	Tire conditions	0.02
	Maintenance of engine	0.01
	Maintenance of fuel tanks	0.01
	Seasonal variations	-
	Σ total epistemic variability	0.08
Aleatoric uncertainties	Σ total aleatoric variability	0.095
Total uncertainty	Total variability	0.175

Here it can be seen that the large variance in the first case has been heavily reduced due to these regulations, where specific measures have been taken. It could also be argued that the driver variability is not relevant in a procurement, which may reduce the uncertainty value even further.

This example shows the possibilities of this methodology, where an open description of the uncertainties may give a larger understanding of the influencing factors and which factors that are possible to reduce. The methodology may as a next step be developed further, to include cases with more parameters and to be adapted to e.g. the EPD-system and efforts should be made to find verified numbers for the input data.

7 Propagation of uncertainties in LCA-calculations

In the previous chapter, the possibility to evaluate the uncertainty of a parameter based on basic definitions of uncertainties was presented and discussed. To find the estimated environmental impact the input parameters are used in some kind of LCA-tool where the final result can be calculated. This chapter shows how the uncertainty of input parameters may propagate in a LCA-calculation, along with the possibilities and limitations in including uncertainties, using the tool developed by Trafikverket, Klimatkalkyl, as a base. This specific tool is based on the EPD-system and uses a web application for the LCA calculations, where the web application is based on previously used Excel-spreadsheets (Toller et al 2015). In this study, Klimatkalkyl version 3.0. has been used, this is not the latest version of Klimatkalkyl, a newer web-based version exists, with the difference being a small update in emission factors. The validity of the demonstration is not affected by this however, since the underlying equations are the same from version 3.0.

As was described in the introduction of this report, Klimatkalkyl only includes certain parts of the life-cycle since it is difficult to assign the emissions from the usage, mainly in form on emissions from traffic, to the structure itself. If such phases were included in the analysis, the results may differ. In this demonstration, only the construction phase and the input materials are included in the LCA since the purpose is to demonstrate the possibility to use probabilistic methods with Klimatkalkyl. It has been shown in other studies that the traffic has a very large impact on the final emissions from the infrastructure, see e.g. Batouli (2017) for a study on the impact of choosing different pavements.

To demonstrate this uncertainty propagation, a case study has been performed. The study is focused on a section of E6 which includes a tunnel and a bridge. This case was chosen due to the interests of the financer Trafikverket/BBT and the project participants. Since no actual uncertainty data is available, the purpose of the case study is to demonstrate effects of including uncertainties for different types of parameters and to compare different uncertainty analysis methods and LCA-models. This has not been done in previous studies, where generic numbers such as the ones used here have only been assigned to the emission factors and not to the other influencing parameters. To find actual uncertainty values, the methodology in the previous chapter may be applied when this has been validated and confirmed.

This chapter includes a description of the cases, followed by a short summary of the used analysis methods, relating to earlier descriptions, and the LCA-models. The chapter is concluded with presentation and analysis of the results.

7.1 Description E6 Bridge and Tunnel

In the case studies original data from Trafikverket has been used based on the planning of a newly built 7.5 km section of the E6 highway in Sweden. The studied road section has a width of 18.5 m with a maximum allowed speed of 110 km/h. It includes a 250 m long tunnel and a 150 m long bridge, 5 shorter bridges, a rest area and a designated turnaround point.

LCA analyses of the tunnel and the main bridge have been carried out using Klimatkalkyl 3.0. The main input data for the calculation is listed in Table 8 and Table 9. The specific environmental impact values for different materials and processes contributing to the Global Warming Potential (GWP) and Cumulative Energy Demand (CED) used in the calculations are listed in Table 10.

Table 8 Tunnel input data.

Materials/processes	Quantity	Unit
Rock excavation	56938	m^3
Cement grouting	38	t
Rock bolts (steel)	12884	m
Shotcrete	13267	m^3
Concrete (cast in place)	6418	m^3
Steel (reinforcement)	320	t
Other materials	5	t
Barrier elements	967	m
Lining (polyester)	10000	m^2
Cable trays (steel)	1000	m

Table 9 Bridge input data.

Materials/processes	Quantity	Unit
Concrete (cast in place)	6250	m^3
Steel (reinforcement)	625	t
Steel (structural)	250	t
Concrete (piles)	500	m

Table 10 Specific environmental impact values.

Materials/processes [unit]	GWP [kgCO_2e/unit]	CED [MJ/unit]
Steel (reinforcement)[kg]	0.72	13.1
Steel (structural)[kg]	1.5	10.1
Steel (galvanized)[kg]	1.87	26.3
Concrete [kg]	0.107	0.75
Cement [kg]	0.715	4.135
Gravel [kg]	0.004	0.103
Polyester [kg]	2.7	78.4
Explosives [kg]	2.5	29.7
Diesel [l]	2.87	39.05
Electricity (Nordic mix) [kWh]	0.0973	1.74

With the specified input parameters, the results using Klimatkalkyl are presented in Table 11. These results could be used as a reference for the probabilistic calculations described in the following subsections. Note that the results are only emissions and energy use related to the construction phase of the bridge and tunnel, no emissions from usage phase are included here.

Table 11 Deterministic results.

	GWP [tCO_2e]		CED [GJ]	
	Total	Per year	Total	Per year
Tunnel	2995.8	28.7	27502.7	265.8
Bridge	2372.2	19.8	23654.4	197.5

7.2 Methods

Two methods have been used to analyze the case studies. First a sensitivity study was carried out "manually", i.e. changing the values of various input parameters in the original LCA model, i.e. the Excel-based Klimatkalkyl. The main idea behind this is that LCA is typically carried out using a software tool, which is often, at least partially, a black box to the user, i.e. not all calculation steps are necessarily transparent and not all aspects of the model can be controlled by the user. In complex cases this could lead to implementation errors which introduce further uncertainties in the process. The results of the sensitivity analysis can be directly used for a VMEA analysis (described in chapter 3) without the need of any complex algorithm or tool.

The second method chosen for the analysis of the case study was Monte Carlo simulation and carried out in Matlab (MathWorks, 2017). The effect of including uncertainties has been analysed at different levels as explained in the next subsection.

7.2.1 Sensitivity analysis and VMEA

A local sensitivity analysis has been performed on the case study regarding the environmental impact of the construction of a bridge. Following the structure of the spreadsheet-based LCA tool by Trafikverket, the environmental assessment of each project (e.g. the construction of a bridge) is based on two quantitative indicators, the "equivalent carbon dioxide", which accounts for the total emissions (in ton) of greenhouse gases released in the atmosphere and the "energy consumption" (in MJ). These two indicators are reported both in their global form (i.e. as a total value for the whole project) and in their "per year" form, thus leading to a set of four outputs to be considered in the analysis. The response of those outputs to small variations in all the inputs having a nonzero nominal value has been the focus of the sensitivity analysis. The nominal values of the inputs have been taken from the spreadsheet itself under the column "utgångsläge".

There exist many possible approaches to sensitivity analysis of computational models and the literature on the subject is vast, see Saltelli et al. (2001) for an introduction. Here, a local One-At-the-Time (OAT) method was used. Each input has been varied by 10% around its nominal value and the following sensitivity coefficients have been evaluated

$$S_{ij} = \left(\frac{\partial Y_i}{\partial X_j}\right)_0 \frac{X_{j0}}{Y_{i0}} = c_{ij}\frac{X_{j0}}{Y_{i0}} \tag{3}$$

where the indexes i, j run over the sets of outputs Y_i and inputs X_j, respectively and Y_{i0} is the output values evaluated at the nominal values of the inputs X_{j0}. The derivative in Eq. 3 has been computed numerically via a central difference formula.

The transparent interpretation and the minimal computational effort required to obtain the sensitivity coefficients have to be balanced to the limitations of this approach, which are intrinsically related to its local nature. The validity of the results of a sensitivity analysis based on those coefficients is confined to relatively small variations of the inputs, where the size of "small" is dependent on the underlying computational model. Furthermore, interactions between inputs are not captured by OAT methods. In order to overcome these limitations, global methods for sensitivity analysis have to be considered, which however present their own drawbacks in terms of computational resources for convergence and possibly uncontrolled assumptions about input distributions. An approach inspired by design-of-experiment techniques can offer a valuable alternative in some cases (Saltelli et al., 2001).

The sensitivity coefficients defined in Eq. 3 can be also seen as the basic building blocks for a local uncertainty analysis, i.e. a method to compute the propagation of uncertainty from inputs to outputs based on the linearization of the response function in the neighborhood of a given nominal point, as suggested in VMEA. The output uncertainty in this framework is expressed through its variance (i.e. second statistical moment) and computed according to the following equation

$$\sigma_{Y_i}^2 = \sum_j c_{ij}^2 \sigma_{X_j}^2, \tag{4}$$

where $\sigma_{X_j}^2$ are the variances of the inputs, which have to be measured or estimated from the available data. Eq. 4 assumes that all the inputs are statistically independent and defines the relative contribution of each input factor to the total uncertainty of the output. No distribution is assumed neither for the input nor for the outputs, contrarily to what happens instead with sampling methods based on Monte Carlo technique or its variants.

7.2.2 Monte Carlo

In the Monte Carlo simulation, the distribution functions of the uncertain parameters need to be defined, yet as shown previously in Table 2, it is the most popular method to include uncertainties in infrastructure LCA. This is because it is relatively simple to use and the computational efforts in LCA are typically not too demanding.

In the studies listed in Table 2 the focus has been on studying the uncertainties in the emission factors. However, as shown in the previous section other type of uncertainties also play an important role and have a significant influence on the results. To illustrate this Monte Carlo simulations have been carried out at different levels of uncertainty considerations. For a more detailed description of the Monte Carlo method, see chapter 4 and e.g. Kroese et al (2011).

7.3 Results and analysis

7.3.1 Sensitivity analysis

In the sensitivity analysis each input variable of the LCA are changed systematically. In the current example Klimatkalkyl was considered as a "black box" and for each input parameter the nominal value was changed by ±10% and the outputs calculated. By this method it possible to quantify the effects of each variable has on the results without considering the underlying calculation steps. Figure 4 and Figure 5 show for the bridge example which input variables actually contribute to the total CO_2 emission and the total energy demand respectively (dashed lines indicate contribution to yearly impact values). This, however might not be clear for the analyst, therefore in the presented case study all variables have been included in the analysis.

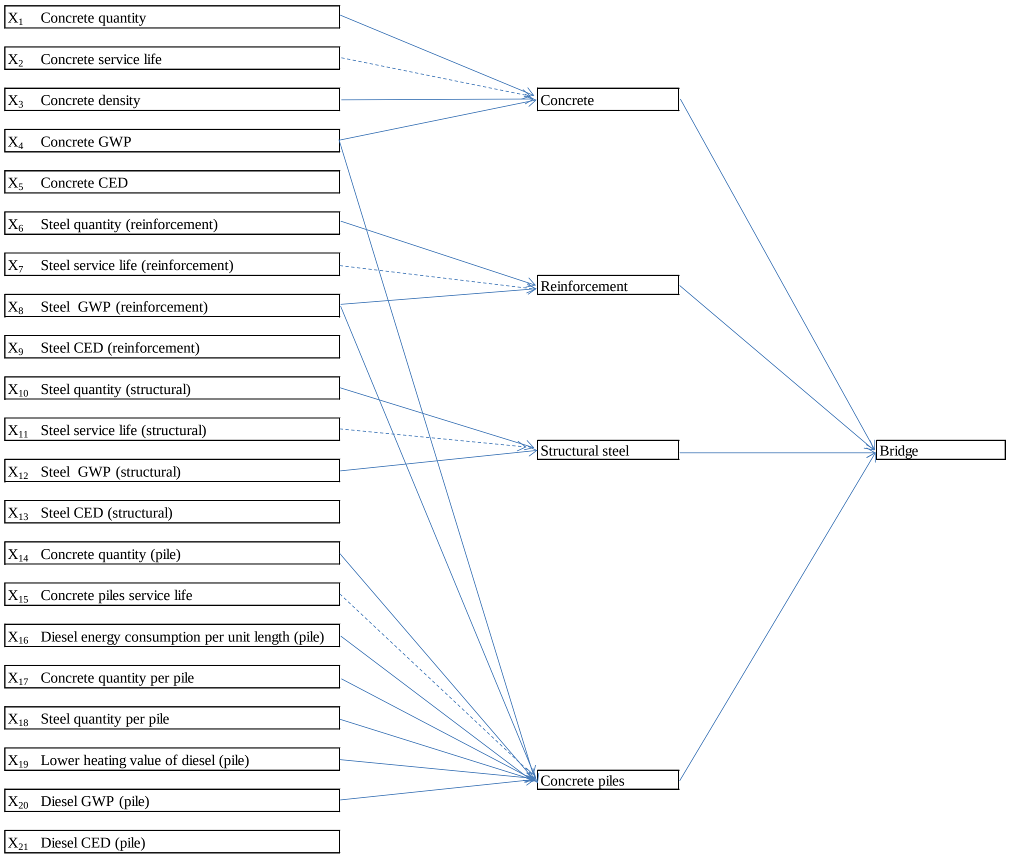

Figure 4 Parameters contributing to total GWP of the bridge.

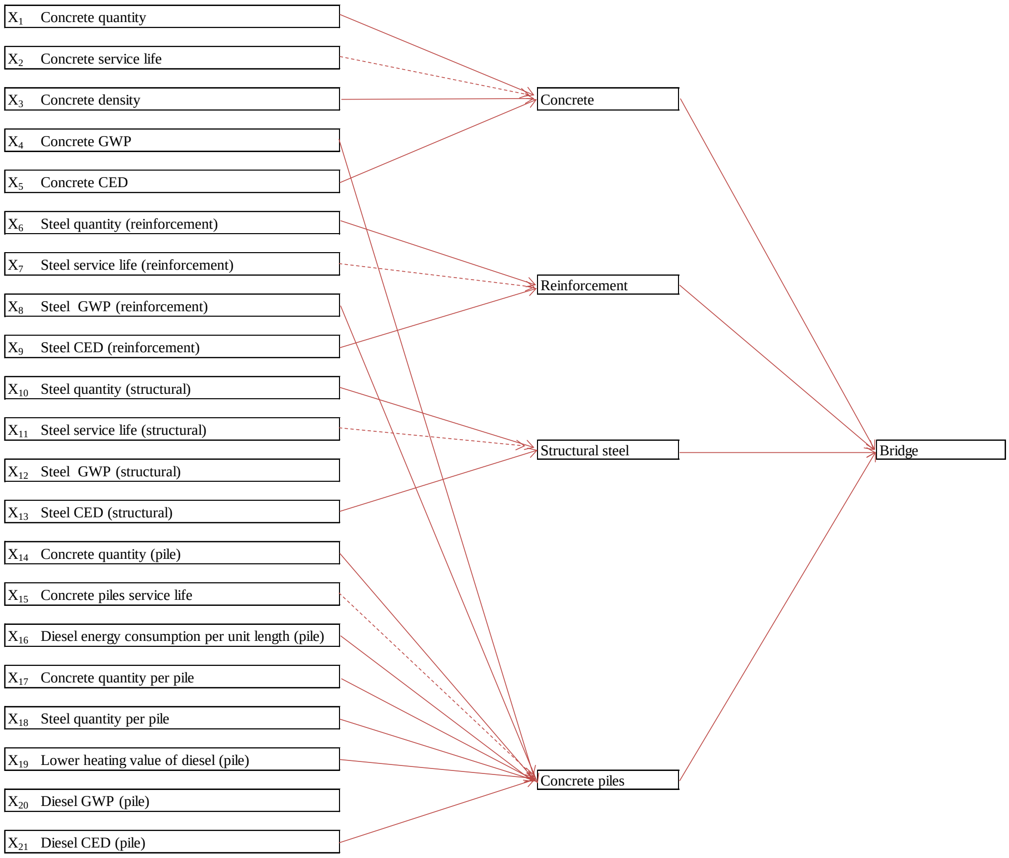

Figure 5 Parameters contributing to total CED of the bridge.

The interpretation of the sensitivity coefficients defined by Eq. 3 is straightforward: the percentage variation of output Y_i with respect to its nominal value (that is obtained by setting all inputs at their nominal values) as input X_j is changed by 10% from its nominal value. The results of a local sensitivity analysis based on the coefficients in Eq. 3 are shown in Figure 6.

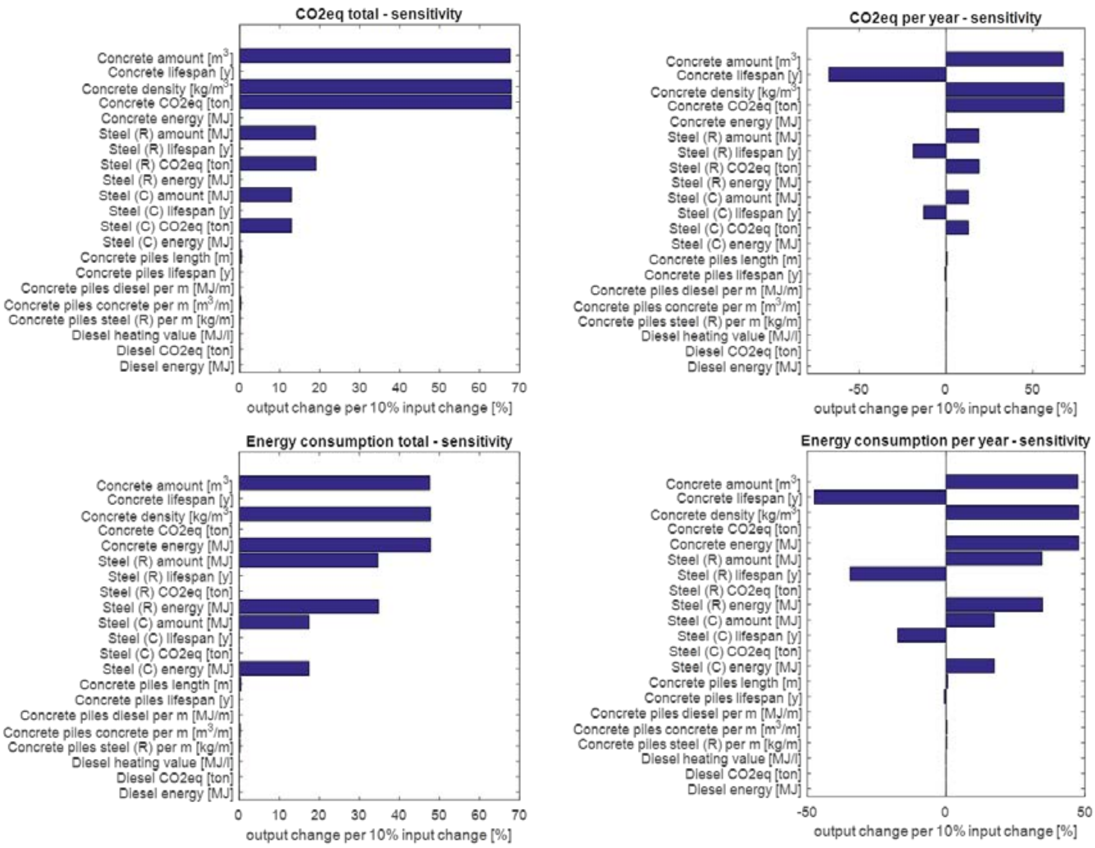

Figure 6 Results of the sensitivity analysis performed on the four outputs of the spreadsheet-based LCA tool by Trafikverket for the bridge case study: (upper row) equivalent CO_2 emissions (total and per year of assumed service life) and (lower row) energy consumption (total and per year of assumed service life). The graphs show the percentage variation in the output with respect to the nominal value for a 10% variation in each input.

7.3.2 VMEA

In the Variation Mode and Effect Analysis the sensitivity factors, determined in the previous sensitivity analysis, were used to sum up the effects of the variations in the input parameters and estimate the total uncertainty. To illustrate the simplicity of the method, it was done in a simple Excel sheet. This provides an easy and transparent way to see how uncertainties propagate from the input to the output. There is no need to define distribution for the uncertain input variables, only the variance need to be determined e.g. based on the method described in chapter 5. The main principle is very similar, however, here the influence of various uncertainties is assumed to be different due to the importance of the parameter.

For the purpose of illustrating the local uncertainty propagation approach, we assumed variances of 0.01 for all inputs (corresponding to a coefficient of variation of 10%) and evaluated the output variance according to Eq. 4. The results are presented in Figure 7.

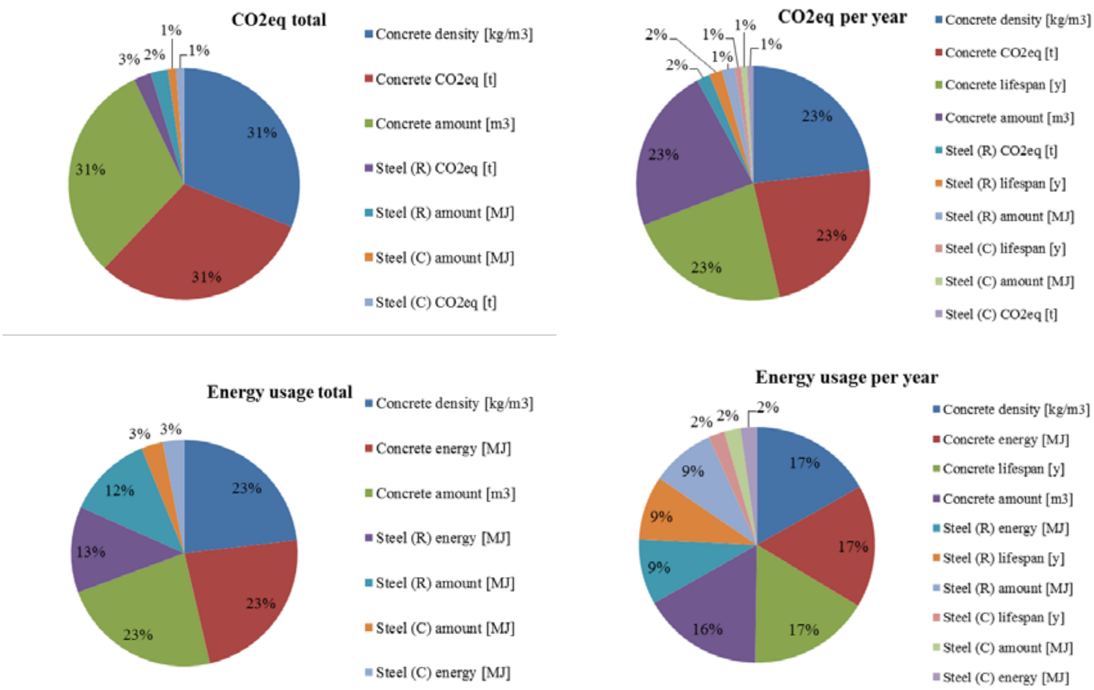

Figure 7 Results of the local uncertainty propagation for the four outputs of the spreadsheet-based LCA tool by Trafikverket for the bridge case study. The figure describes how much influence each parameter has on the final result.

With the obtained sensitivity coefficients, the total variation can easily be calculated and the effect of the uncertainties studied. This is illustrated in Table 12 and Table 13, where the uncertainties are summed up according to Eq. 4 and the standard deviation for the LCA output is estimated.

Table 12 VMEA calculation table (total GWP of the bridge).

CO_2eq total [t]	**Value**	**COV**	**Standard deviation**	**Sensitivity coefficient**	**Uncertainty**
			σ	c	$c^2\sigma^2$
Concrete quantity	6 250,00	0,1	625,00	0,2568	25760,250
Concrete service life	120,00	0,1	12,00	0,0000	0,000
Concrete density	2 400	0,1	240,00	0,6717	25987,439
Concrete GWP	0,11	0,1	0,01	15066,0000	25987,439
Concrete CED	0,75	0,1	0,08	0,0000	0,000
Steel quantity (reinforcement)	625,00	0,1	62,50	0,7200	2025,000
Steel service life (reinforcement)	120,00	0,1	12,00	0,0000	0,000
Steel GWP (reinforcement)	0,72	0,1	0,07	628,1500	2045,463
Steel CED (reinforcement)	13,10	0,1	1,31	0,0000	0,000
Steel quantity (structural)	205,00	0,1	20,50	1,5000	945,562
Steel service life (structural)	120,00	0,1	12,00	0,0000	0,000

Steel GWP (structural)	1,50	0,1	0,15	205,0000	945,562
Steel CED (structural)	20,10	0,1	2,01	0,0000	0,000
Concrete quantity (pile)	500,00	0,1	50,00	0,0195	0,950
Concrete piles service life	80,00	0,1	8,00	0,0000	0,000
Diesel energy consumption per unit length (pile)	10,18	0,1	1,02	0,0407	0,002
Concrete quantity per pile	0,06	0,1	0,01	128,4000	0,499
Steel quantity per pile	6,30	0,1	0,63	0,3600	0,051
Lower heating value of diesel (pile)	35,20	0,1	3,52	-0,0118	0,002
Diesel GWP (pile)	2,87	0,1	0,29	0,1446	0,002
Diesel CED (pile)	39,05	0,1	3,90	0,0000	0,000
Total			**289,31**		*83698,221*

Table 13 VMEA calculation table (GWP per year of the bridge).

CO_2eq per year [t/y]	**Value**	**COV**	**Standard deviation**	**Sensitivity coefficient**	**Uncertainty**
			σ	c	$c^2\sigma^2$
Concrete quantity	6 250,00	0,1	625,00	0,0021	1,789
Concrete service life	120,00	0,1	12,00	-0,1115	1,789
Concrete density	2 400	0,1	240,00	0,0056	1,813
Concrete GWP	0,11	0,1	0,01	125,8250	1,813
Concrete CED	0,75	0,1	0,08	0,0000	0,000
Steel quantity (reinforcement)	625,00	0,1	62,50	0,0060	0,141
Steel service life (reinforcement)	120,00	0,1	12,00	-0,0313	0,141
Steel GWP (reinforcement)	0,72	0,1	0,07	5,2477	0,143
Steel CED (reinforcement)	13,10	0,1	1,31	0,0000	0,000
Steel quantity (structural)	205,00	0,1	20,50	0,0125	0,066
Steel service life (structural)	120,00	0,1	12,00	-0,0214	0,066
Steel GWP (structural)	1,50	0,1	0,15	1,7083	0,066
Steel CED (structural)	20,10	0,1	2,01	0,0000	0,000
Concrete quantity (pile)	500,00	0,1	50,00	0,0002	0,000
Concrete piles service life	80,00	0,1	8,00	-0,0015	0,000
Diesel energy consumption per unit length (pile)	10,18	0,1	1,02	0,0005	0,000
Concrete quantity per pile	0,06	0,1	0,01	1,6050	0,000
Steel quantity per pile	6,30	0,1	0,63	0,0045	0,000
Lower heating value of diesel (pile)	35,20	0,1	3,52	-0,0001	0,000
Diesel GWP (pile)	2,87	0,1	0,29	0,0018	0,000

Diesel CED (pile)	39,05	0,1	3,90	0,0000	0,000
Total			**2,80**		*7,825*

7.3.3 Monte Carlo

In the Monte Carlo simulations, first only the uncertainties in the emissions were considered and the overall uncertainties in the final result were calculated. Second, the uncertainties in the quantities, i.e. how much from the different materials are needed, were added as well. Finally, the uncertainties of the assumed service life of different construction elements were also treated as random variables. Table 14 and Table 15 shows the results of the analysis in case of the bridge and the tunnel.

For the sake of simplicity, it was assumed that all variables are normally distributed and that the coefficient of variation is 0.1. Furthermore, all the variables were assumed statistically independent, which is most likely not true.

As expected the standard deviation of the results increases significantly when more uncertainties are included as shown in Figure 8 for the bridge case. Interestingly the mean value increases slightly as well. This shows the importance of including uncertainties for all influencing parameters and not only the emission factors themselves, even though it is difficult to assess the magnitude of this influence using only generic values for the uncertainty. It can also be seen from Tables 14 and 15 that the standard deviation for the results from the tunnel case is larger than for the bridge. This is due to the larger number of parameters for the tunnel, and is a direct consequence of the assumption of equal variation for all parameters.

Table 14 MC results for the bridge.

	GWP [tCO_2e/year]		**CED [GJ/year]**	
	mean	std.	Mean	std.
Include uncertainties of the emissions	19.82	1.42	197.56	12.19
Include uncertainties of the quantities as well	19.80	2.01	197.46	17.15
Include uncertainties of the lifetimes as well	20.01	2.94	199.26	27.28

Table 15 MC results for the tunnel.

	GWP [tCO_2e/year]		CED [GJ/year]	
	mean	std.	Mean	std.
Include uncertainties of the emissions	28.88	1.80	262.86	13.59
Include uncertainties of the quantities as well	28.92	2.32	262.73	17.66
Include uncertainties of the lifetimes as well	29.19	3.18	265.76	26.32

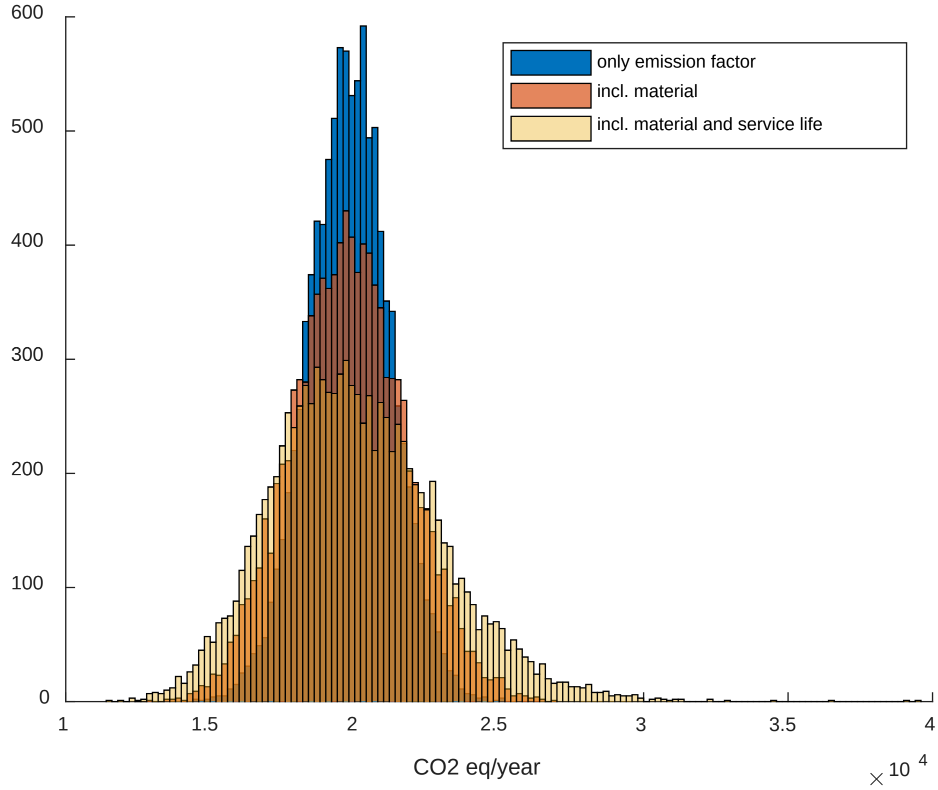

Figure 8 Histograms of the three different levels of uncertainty consideration for the bridge case. The blue bars only include uncertainties in the emission factors, while the lightest yellow bars include uncertainties for all three levels (emission factors, material amounts, expected service life).

It is interesting to compare the Monte Carlo results with those obtained using VMEA. Therefore, the standard deviations of the VMEA results have been calculated for the same levels as in the Monte Carlo simulations presented above. The results of the comparison are given in Table 16. It can be seen that the standard deviations for both methods are similar when including uncertainties for emission factors and material amounts. The main difference is if the uncertainty in the expected service life is included. Then the standard deviation for the results from the Monte

Carlo simulation is much larger than the one from VMEA, which shows the difference between the two methods.

Table 16 Comparison of VMEA and MC results for the bridge case.

	GWP std [tCO_2e/year]		CED std [GJ/year]	
	VMEA	MC	VMEA	MC
Include uncertainties of the emissions	1,42	1,42	12,17	12,19
Include uncertainties of the quantities as well	2,00	2,01	17,16	17,15
Include uncertainties of the lifetimes as well	2,45	2,94	20,99	27,28

8 Applied source-based uncertainty analysis of an existing LCA model

8.1 Background and principles for the analysis

As previously stated in the study, an analysis of uncertainties is not a completely unambiguous concept but a complex analysis of different types of uncertainties. It is therefore not about finding an uncertainty for the whole system, but rather about analyzing the various uncertainties and variations that may exist and the reason for them. When assessing a dataset with its uncertainties, it is also important to make an assessment of which uncertainties and variations may be relevant to include in a comparison. Variations of diesel consumption on a construction site during excavation can after all show great variations. Are all these variations the result of uncertainties to be considered? Here, there are variations that depend on everything from measurement uncertainties for the diesel pump when refueling to rain in the workplace, which makes it muddy and slippery, hilly terrain or the drivers' different personal driving patterns. Are all these examples of uncertainties to be considered in a comparison. Can there be reasons to standardize different uncertainties?

The theoretical aspects of this have been discussed earlier in this study. In this chapter, we will examine how these uncertainties and variations behave in a practical application where one can analyze different types of uncertainties and its impact on all or parts of the system. For this purpose, we have chosen an LCA model in the construction industry that illustrates many typical processes, and which constitute heavy and important tasks such as soil preparation (e.g. forest harvesting, clearing), excavation, rock and soil cutting, and ground stabilization with various techniques. The LCA model chosen as an illustration for this example is the foundation for a railway track, which is described further below.

8.2 Description of the test model

The test model is an LCA model of foundations for railway tracks. The model is detailed and contains most of the processes included in foundation works. The model is dynamic, so it can be adapted to many different conditions and process choices. It also includes possibilities for uncertainty evaluation with variation of uncertainty span for variables and Monte Carlo simulations. The model is a linear mathematical matrix with an equal number of variables and equations. In the list on the next page, different details about the model is presented.

6107 variables

6107 equations

of which

(4902 in modules)

(1112 in transports)

(93 in junctions)

287 modules

139 transport modules

16 input junctions

57 output junctions

409 flows

6 text objects

1109 variable names

5 modes of conveyance

The outline of the model is shown in Figure 9 and Figure 10. The model consists of three parts, Construction (green), Operation (blue) and Maintenance (red) of which Operation does not include any activities because a foundation in this context is just the bearing part under the railway track. These parts are connected into one model. The maintenance of the foundation is calculated based on process activities and lifetime of the different components in the foundation. The maintenance activities are then distributed as a yearly addition to achieve a comparable result, which is independent of length of the calculation period. In this case, a calculation period of 60 years has been used and the length of the foundation is 1000 m.

Figure 9 Railway track foundation model structure. Construction part. The model continues in the next figure. (Use pdf file and read figure from screen for improved readability).

Figure 10 Railway track foundation model structure. Operation and maintenance part. Continued from previous figure. (Use pdf file and read figure from screen for improved readability).

8.3 Analysis of the LCA model

8.3.1 Input and output results from the entire system without uncertainties

In order to obtain an overview of the entire model, Table 17 presents all input and output data for the foundation model. The data refer to 1000 m railway track foundation with a typical specification in south Sweden or northern Europe. No tunnel or bridges are included. As can be seen, there are many different inputs and outputs and it can thus be difficult to get an overview of the uncertainties for all these variables. An analysis can therefore begin with some selected but strategically important variables that can be analyzed in more detail to get an idea of the dynamics of the system model. Significant variables can e.g. be variables that are common, that occur in large quantities or that have a significant environmental impact even in small quantities. Examples of such variables can be energy variables, important raw materials or significant emissions such as CO_2, NO_X, SO_2, Hg, Cd, Pb etc. In a pure variable analysis, each variable can be analyzed with its uncertainty interval, for example with a Monte Carlo method. The uncertainty interval will then be affected by all the equations in the model that include that variable, but it can indirect also be affected by other variables that interact with the variable that is the subject of the uncertainty analysis. In this analysis, we will exemplify these cases. However, in composite variables such as Global Warming Potential (GWP) or Acidification, the uncertainties are aggregated from the variables included in the composite calculation and can thus be calculated on the basis of the statistical calculation rules for uncertainties that exist, and the calculation equation used for the respective composite variable. In this study, we will only focus on the uncertainties of the pure variables and its behavior.

Table 37 Input and output results from the entire system without uncertainties for 1000 m railway track foundation.

SUMMARY OF Entire system			
Variable:	**Inputs:**	**Outputs:**	**Unit:**
<Chemicals>			
Ammonia	0.002779		kg
CaO (chem)	0.7122		kg
$CaSO_4$ (chem)	0.03477		kg
Cyklohexylamine	0.0007209		kg
Gypsum, residual product	1642		kg
H_2SO_4 (chem)	1.188		kg
HNO_3 (chem)	0.000186		kg
Hydrazine, N_2H_4	0.003605		kg
Moth agent	15.33		kg
NaCl (chem)	1.408		kg
Nitrogen, N_2	271.6		kg

O_2 (chem)	8.281		kg
Oxygen, O_2	464.9		kg
Slag, blast furnace	218.9		kg
<Emissions to air>			
Alkane (air)		0.0006312	kg
As (air)		0.0002504	kg
Benzene (air)		0.001021	kg
Benzo(a)pyrene (air)		6.21E-06	kg
Butane (air)		0.0007333	kg
C 14 (air)		427.2	kBq
CCl4 (air)		1.85E-06	kg
Cd (air)		0.0007075	kg
CF4 (air)		2.69E-05	kg
CFC 11 (air)		5.36E-06	kg
CFC 114 (air)		0.0005156	kg
CFC 12 (air)		0.000112	kg
CFC/HCFC (air)		0.01587	kg
CH_4 (air)		206.3	kg
Cl_2 (air)		4.99E-05	kg
CO (air)		687.2	kg
CO_2 biogenic (air)		1007	kg
CO_2 biogenic (deforestation)		4.22E+04	kg
CO_2 biogenic (soil)		7913	kg
CO_2 fossil (air)		2.33E+05	kg
CO_2 uptake concrete		-2955	kg
Cr (air)		0.0005397	kg
Cr VI (air)		5.27E-06	kg
Cu (air)		0.007867	kg
Ethane (air)		0.001063	kg
Ethene (air)		0.0004265	kg
H_2S (air)		0.003033	kg
H_2SO_4 (air)		0.003566	kg

Halon 1211 (air)		3.21E-07	kg
Halon 1301 (air)		3.65E-07	kg
HC (air)		152.8	kg
HC aromatic (air)		0.694	kg
HCFC 22 (air)		0.0002609	kg
HCl (air)		0.7358	kg
HCN (air)		2.23E-06	kg
Hexachlorobenzene (air)		2.28E-08	kg
Hexane (air)		0.0003561	kg
HF (air)		0.03885	kg
Hg (air)		0.0005634	kg
Kr 85 (air)		178.9	kBq
N_2O (air)		12.1	kg
NH_3 (air)		3.386	kg
Ni (air)		0.03005	kg
NMVOC (air)		96.8	kg
NO_X (air)		1591	kg
O_3 (air)		0.0004836	kg
PAH (air)		0.0004009	kg
Particles (air)		91.14	kg
Particles 2.5 to10 (air)		0.7841	kg
Particles <2.5 (air)		0.2951	kg
Particles >10 (air)		1.079	kg
Pb (air)		0.03247	kg
Pentane (air)		0.0009182	kg
Phenol (air)		9.85E-05	kg
Propane (air)		0.000717	kg
Radioactive emissions		8.29E+08	kBq
Rn 222 (air)		4505	kBq
Rn-222		7.33E+05	Bq
Sb (air)		4.76E-06	kg
Se (air)		0.000107	kg

SF_6 (air)		0.0001705	kg
SO_2 (air)		204.3	kg
TCDD eqv. (air)		3.94E-08	kg
Tl (air)		0.003152	kg
VOC (air)		1.55	kg
Xylenes (air)		0.0001947	kg
Zn (air)		0.02805	kg
<Emissions to soil>			
Oils, unspecified (soil)		0.04288	kg
<Emissions to water>			
Acids as H ion (aq)		0.01755	kg
Al (aq)		0.3589	kg
AOX (aq)		3.52E-06	kg
As (aq)		0.002486	kg
Benzene (aq)		0.0003704	kg
BOD (aq)		0.9981	kg
Br (aq)		0.002679	kg
Carbonate ions (aq)		0.2838	kg
Cd (aq)		0.009098	kg
Chloride ions (aq)		0.03165	kg
Cl ions (aq)		237.6	kg
CN ions (aq)		0.009685	kg
Co (aq)		0.0004969	kg
COD (aq)		624.1	kg
Cr (aq)		0.01541	kg
Cr VI (aq)		0.0004471	kg
Cu (aq)		0.003883	kg
Detergent/oil (aq)		0.06291	kg
Dissolved organics (aq)		0.07749	kg
Dissolved solids (aq)		0.2225	kg
DOC (aq)		0.261	kg
F (aq)		0.2945	kg

Fe (aq)		0.1607	kg
H_2S (aq)		6.37E-05	kg
HC (aq)		0.05503	kg
HC aromatic (aq)		0.001771	kg
HC chlorinated (aq)		0.0003295	kg
Hg (aq)		0.008613	kg
Lead Pb (aq)		2.65E-05	kg
N, excl. NH_3 (aq)		-0.03089	kg
N, total (aq)		3.123	kg
Na (aq)		0.004943	kg
NaClO (aq)		0.007815	kg
NH_3/NH_4 (aq)		3.395	kg
Ni (aq)		0.004034	kg
Nitrate (aq)		0.08758	kg
Nitrite (aq)		0.0002843	kg
Oil, unspec. (aq)		12.6	kg
Organics (aq)		6.234	kg
P as P_2O_5 (aq)		0.0648	kg
P, total (aq)		1.156	kg
PAH (aq)		2.22E-05	kg
Pb (aq)		0.007704	kg
Phenol (aq)		0.06522	kg
Phosphate (aq)		0.02576	kg
Radioactive emissions (aq)		7.82E+06	kBq
Sb (aq)		6.97E-06	kg
Sn (aq)		0.5452	kg
SO_3 ions (aq)		0.004828	kg
SO_4 ions (aq)		15.41	kg
Sulphate ions (aq)		0.7172	kg
Sulphide (aq)		0.0004763	kg
Sulphides (aq)		0.3146	kg
Sulphur/sulphide		0.5683	kg

Suspended solids (aq)		3.887	kg
TOC (aq)		0.3635	kg
V (aq)		0.001631	kg
waste water		302.1	kg
Zn (aq)		0.03881	kg
<Energy carriers>			
Biomass fuels		9788	MJ
Energy steam/heat		2781	MJ
Energy steam/heat gain		650.1	MJ
<Energy resources non-renewable>			
Coal	2.07E+05		MJ
Crude oil	2.29E+06		MJ
Energy unspecified	-1.18E+04		MJ
Natural gas	3.78E+05		MJ
Nuclear	2.46E+05		MJ
Peat	91.06		MJ
<Energy resources-renewable>			
Biomass fuel	1.10E+04		MJ
Hydro power	7.55E+04		MJ
Solar power	0.0004788		MJ
Wind power	7461		MJ
<Materials/Products>			
Al (recycled)	0.02599		kg
Ballast, crushed (m^3)	2750		m^3
Biomass (dry substance)		4.60E+04	kg
Blast stone fill railway terrace	1500		m^3
Blast stone filling m3	2229		m^3
Concret Culvert 1000 mm		60	m
Concret Culvert 400 mm		7.5	m
Concrete kg		1.69E+05	kg
Concrete m^3		203.2	m^3
Cu (recycled)	0.2983		kg

Fe (recycled)	2.15		kg
Ferrous scraps	1.94E+04		kg
limestone	1.325		kg
Manhole (1200) length		2.94	m
Manhole (1500) length		1.575	m
Manhole (600) length		2.34	m
Pit run gravel & sand	0		kg
Protection fences		150	m
Rock wool	0.2471		kg
Soil		1.11E+07	kg
Soil fill railway terrace	200		m^3
Soil filling m^3	7835		m^3
Wood	0.2439		kg
Wood, dimensional lumber		3.915	m^3 sp
<Miscellaneous>			
Area	9000		m2
CO_2 max uptake concrete		-5.91E+04	kg
Dumper trp Lm^3 x km	1.89E+04		Lm^3*km
<Process operations>			
Cable channels		750	m
Noise protection length		45	m
Rock wall bolting area		75	m^2
<Process parameters>			
Drillmeter hole	511.5		m
<Resources>			
Mn (res)	0.781		kg
Mo (res)	0.01462		kg
Ni (res)	0.3383		kg
<Resources non-renewable>			
Al (res)	1.064		kg
Anhydrite $CaSO_4$	164.2		kg
Baryte $BaSO_4$	0.3429		kg

Basalt	0.2901		kg
Basalt (res)	0.01557		kg
Bauxite AlO(OH)	437.9		kg
Bentonite	0.4284		kg
Bentonite (res)	6.738		kg
Calcite, $CaCO_3$	271.4		kg
Cr (res)	0.112	0.001696	kg
Cu (res)	1.198		kg
Dolomite $CaMg(CO_3)_2$	181.8		kg
Fe (res)	9991		kg
Feldspar (res)	4.91E-07		kg
Fluorspar CaF_2	0.009726		kg
Fluorspar CaF_2 (res)	0.3062		kg
Gypsum	2408		kg
Gypsum (res)	3.76E-05		kg
Iron sulphate	383.1		kg
KCl (res)	0.01689		kg
Limestone $CaCO_3$	1.53E+05		kg
Mg (res)	0.09374		kg
NaCl (res)	64.84		kg
Natural sand and gravel	0.00033		kg
Olivine $(Mg,Fe)_2SiO_4$	0.01821		kg
Olivine (res)	1.23E-05		kg
Pb (res)	18.94		kg
Rutile, TiO_2	0.009358		kg
S (res)	0.006199		kg
Sand and gravel	1.98E+05		kg
Shale	0.1037		kg
Silica sand SiO_2	367		kg
Sn (res)	7.53E-05		kg
Soil and till (res)	268.7		kg
Solid rock	2.37E+07	4.46E+06	kg

Stone and sand (res)	548.9		kg
Sulphur (bonded)	0.05604		kg
Sulphur (elemental)	0.115		kg
TiO_2 (res)	0.007209		kg
Zn (res)	56.25		kg
Zr (res)	0.0224		kg
<Resources-renewable>			
Freshwater (res)	483.2		kg
Groundwater (res)	90.39		kg
Land use	4.43E+04		m^2
Sea water (res)	65.49		kg
Water	2.07E+05		kg
Water for cooling	2.08E+05	2.08E+05	kg
Water unspecified (res)	1.24E+05		kg
Wood kg (res)	9.689		kg
Wood kg DS (res)	2467		kg
Wood m^3 (res)	100		m^3
<Specifications>			
Carbon content		2.16E+05	kg
Carbon oxidized		2156	kg
Foundation length		1000	m
<Wastes, solid>			
Al to recycling		0.05029	kg
Concrete to recycling		7.84	kg
Cu to recycling		0.2742	kg
Depleted U as UF_6		0.3468	kg
EAF slag compl prod		1305	kg
Hazardous to incineration		0.3324	kg
Hazardous to landfill		0.5936	kg
High radioactive waste		7.61E-08	m^3
Inert chemicals		0.007586	kg
Low Medium radioactive		5.20E-09	m3

Low radioactive no treatment		479.4	kg
Low radioactive waste		2.01E-07	m^3
Medium radioactive waste		7.61E-09	m^3
Pb to recycling		0.02556	kg
Radioactive demolition waste		2.24E-07	m^3
Radioactive waste		3.11E-09	m^3
Regulated chemicals		0.462	kg
Slag and Ash		93.4	kg
Spent nuclear fuel		0.05035	kg
Steel to recycling		13.07	kg
Uranium in spent fuel		0.03468	kg
Waste to incineration		2.972	kg
Waste to landfill		544.5	kg
Waste to recycling		1.383	kg
Waste, concrete		3.25E+05	kg
Waste, construction		2.098	kg
Waste, demolition (inactive)		0.4964	kg
Waste, glass		326	kg
Waste, hazardous		9.584	kg
Waste, highly radioactive		0.3514	kg
Waste, industrial		2458	kg
Waste, mineral		396.9	kg
Waste, other		787	kg
Waste, polyethene		4950	kg
Waste, radioactive		1.347	kg
Waste, reg. chem.		14.08	kg
Waste, steel		1.08E+04	kg
Waste, wood		1175	kg
Zn to recycling		0.001259	kg

In an application like in this example, the energy use is important and especially the diesel use for all the machines. An analysis of the use of primary energy in the table above shows the following energy distribution in Table 18, which can be used for the further analyses:

Table 18 Energy distribution for Primary energy resources used in the LCA model.

Primary energy resources	Used share (%)
Coal	6.4 %
Crude oil	71.3 %
Natural gas	11.8 %
Nuclear	7.6 %
Peat	0.0028 %
Biomass fuel	0.3 %
Hydro power	2.3 %
Solar power	0.000000015 %
Wind power	0.2 %

As shown from the distribution of the energy resource use above, the use of crude oil is the most important factor.

1.1.1 Aleatoric uncertainties

The aleatoric uncertainties represent the most fundamental uncertainties that always will be included and that cannot be improved by better measurements or data in a normal application. For the use of crude oil, the measurement uncertainty of the volume/mass has, in this case, been identified as an important aleatoric uncertainty. The measurement uncertainty of the fuel volume is usually about ±0.5 % of the measured volume, which has been used in the uncertainty calculations. In Table 19, some estimated aleatoric measurement uncertainties are presented for a selected number of parameters, to be used in the further analyses. For uncertainties in other parameters and equations, an estimated standard uncertainty of ±5 % has been used.

Table 19 Used aleatoric measurement uncertainties, estimated for some selected variables.

Parameter	Used aleatoric measurement uncertainties
Energy input	
Crude oil	±0.5 %
Natural gas	±2 %
Coal	±1 %
Biomass	±1 %
Electricity	
Hydro power	±2 %

Nuclear power	±2 %
Solar power	±2 %
Wind power	±2 %
<u>Emissions</u>	
CO_2	±3 %
NO_X	±3 %
SO_2	±7 %
N_2O	±3 %
CH_4	±3 %
Other parameter/equations	±5 %

In an LCA model like in this example, there is a possibility to include uncertainties for all variables and equations. This is of course time consuming and require uncertainty data for all the variables, which can be difficult to achieve. In addition, in a model like this, not all variables take part in all equations and thus not all variables affect all other variables. This means that a selection of variables and equations can be done in order to analyze a specific variable and its uncertainty behavior. This method has been used for the uncertainty calculations in this example. In fact, two different equation selections have been used; consisting of only equations that include the parameter to be analyzed and a second part including all equations and variables that in some way affect the parameter to be analyzed. The latter analysis is the one in the result boxes with the higher number of parameters taken part in the uncertainty analysis. In this analysis, the above estimated aleatoric uncertainties are used to calculate a Monte Carlo simulation of the input and output variables in the model when a random variation span (used from Table 19) is included in the model equations. The model equation system is solved 8000 times with different random normal distributed uncertainty intervals. The results for the different input or output parameters to be studied are presented in a result box with a distribution for each parameter and different statistic information for each distribution. The number of parameters that took part in each uncertainty calculation is also included in the result boxes.

In the result boxes below (Figure 11 to Figure 17), the results from the uncertainty analyses of some selected parameters (Crude oil, CO_2 fossil (air), NO_X (air) and SO_2 (air)) are shown. As can be seen from the result boxes, the uncertainty interval for the aleatoric uncertainties can be relatively small when only the primary equations are considered. When all affecting parameters/equations are considered, the uncertainty can increase considerably up to over ±6 %. The effects of the secondary equations are in this model substantial and the estimated standard uncertainty of ±5 % for the secondary affecting variables/equations contributes strongly to the specific overall uncertainty level.

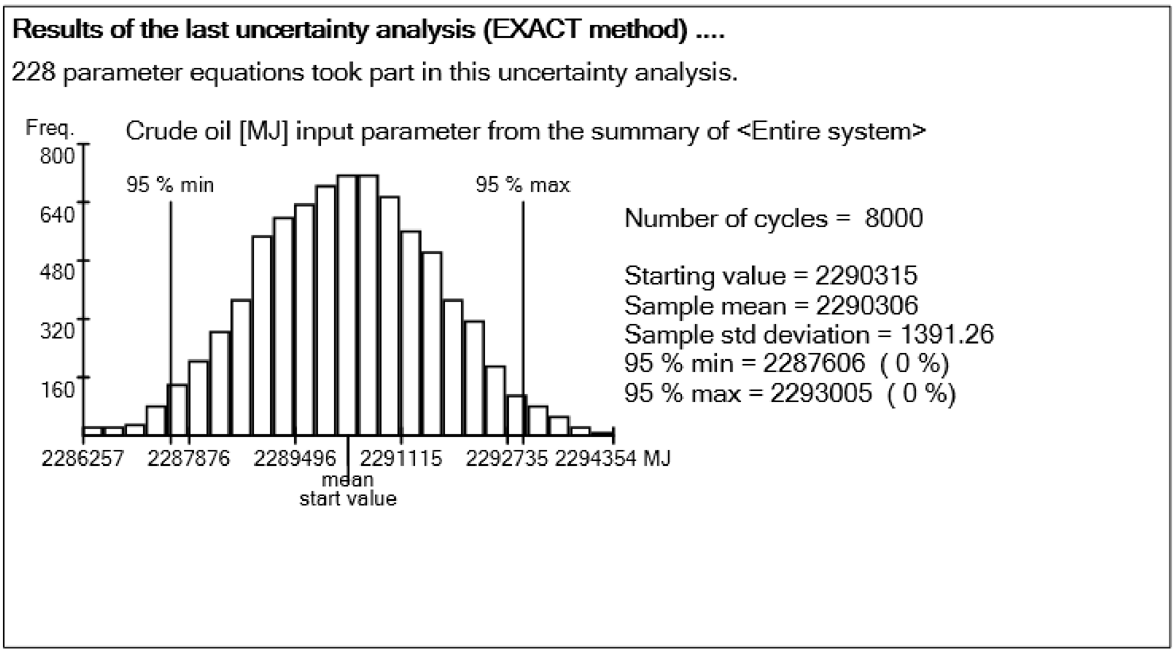

Figure 10 Estimated aleatoric uncertainty for the input variable Crude oil to the system. The figure shows uncertainties based on equations containing the variable Crude oil.

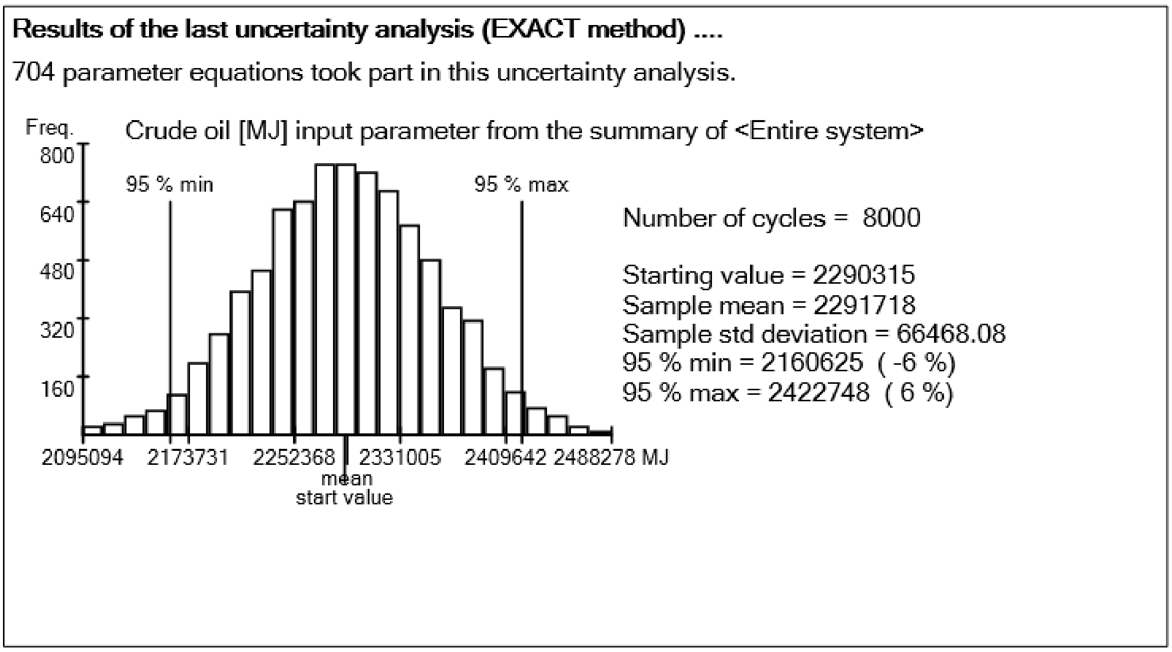

Figure 11 Estimated aleatoric uncertainty for the input variable Crude oil to the system. The figure shows uncertainties based on all equations affecting the variable Crude oil.

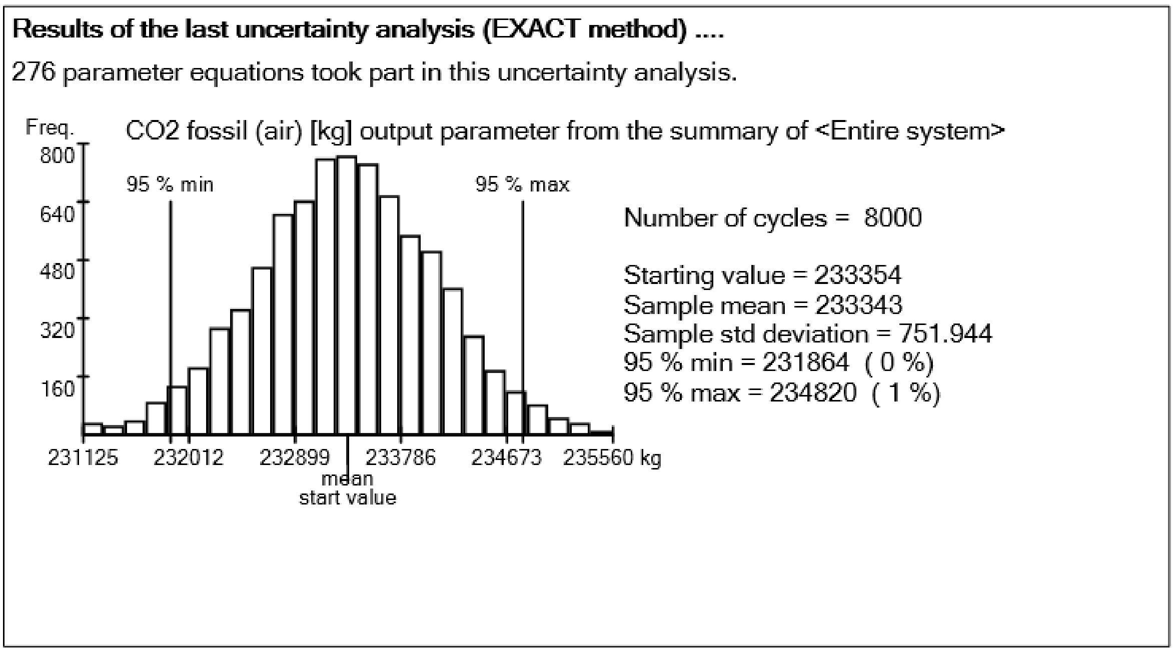

Figure 12 Estimated aleatoric uncertainty for the output variable CO_2 fossil (air) from the system. The figure shows uncertainties based on equations containing the variable CO_2 fossil (air).

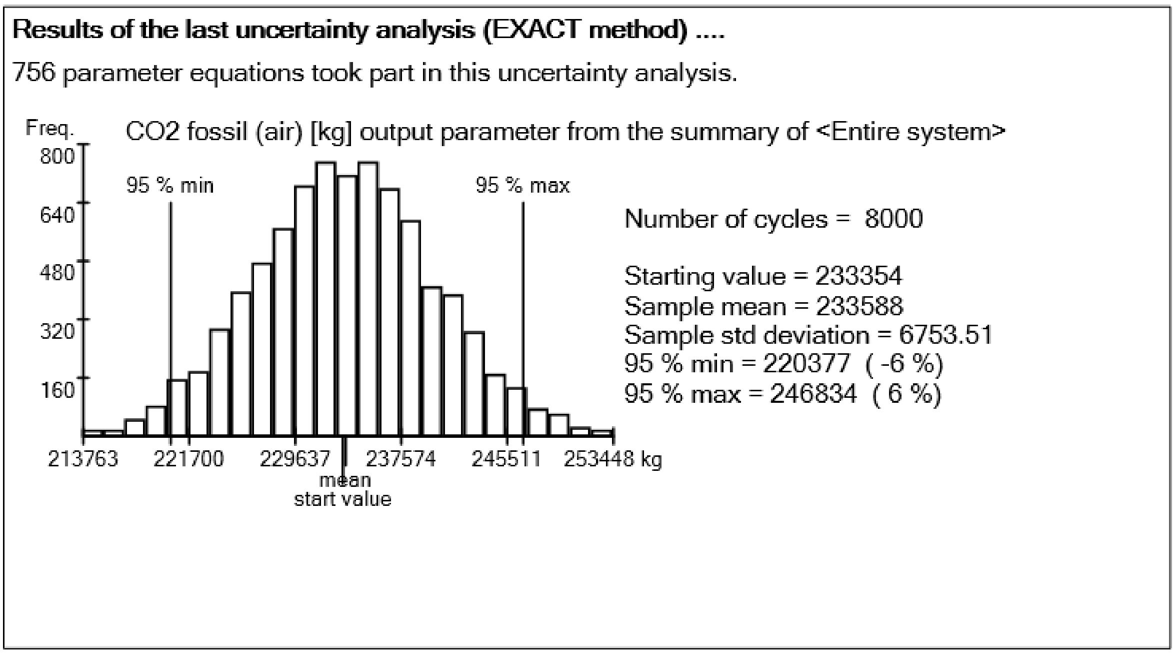

Figure 13 Estimated aleatoric uncertainty for the output variable CO_2 fossil (air) from the system. The figure shows uncertainties based on all equations affecting the variable CO_2 fossil (air).

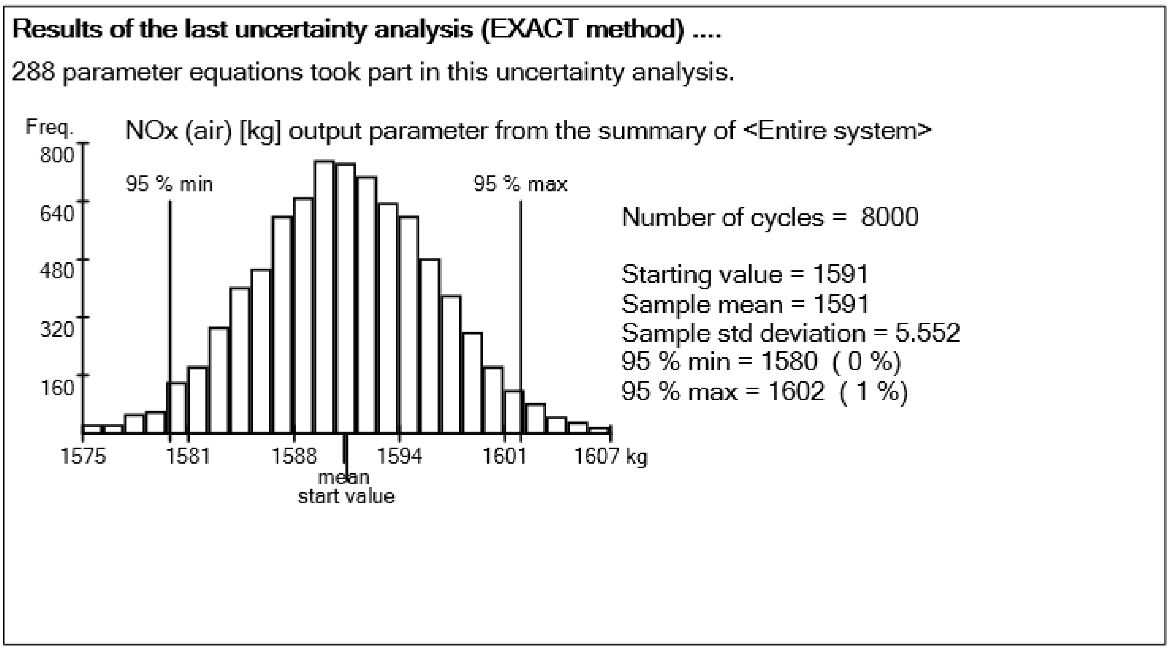

Figure 14 Estimated aleatoric uncertainty for the output variable NO_X (air) from the system. The figure shows uncertainties based on equations containing the variable NO_X (air).

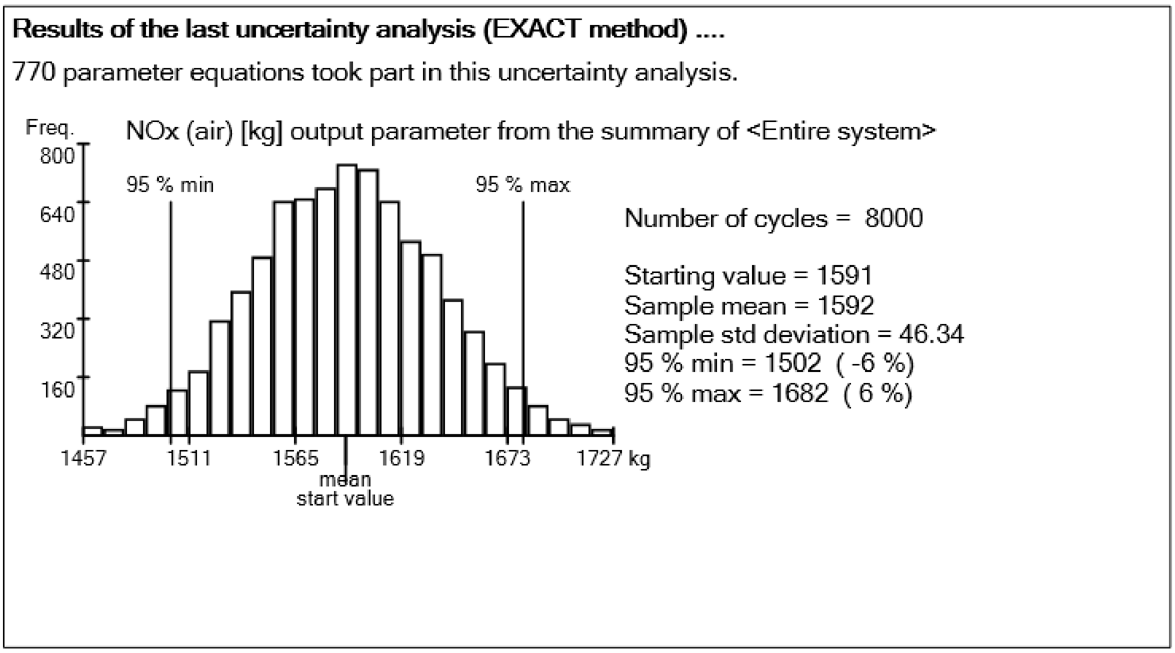

Figure 15 Estimated aleatoric uncertainty for the output variable NO_X (air) from the system. The figure shows uncertainties based on all equations affecting the variable NO_X (air).

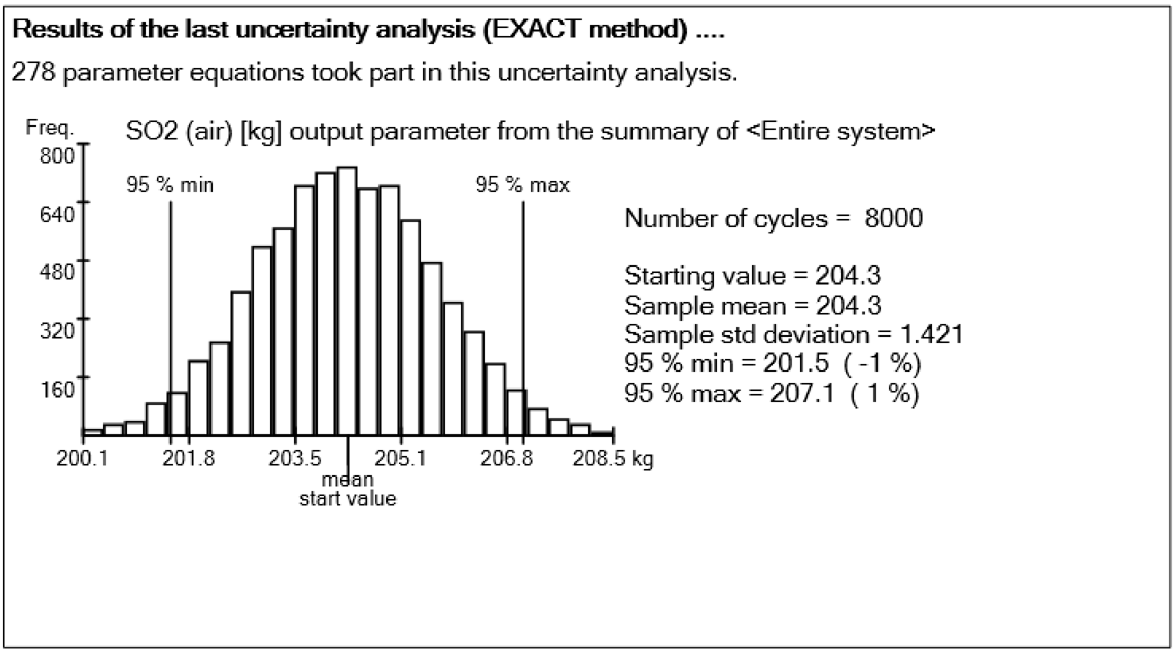

Figure 16 Estimated aleatoric uncertainty for the output variable SO_2 (air) from the system. The figure shows uncertainties based on equations containing the variable SO_2 (air).

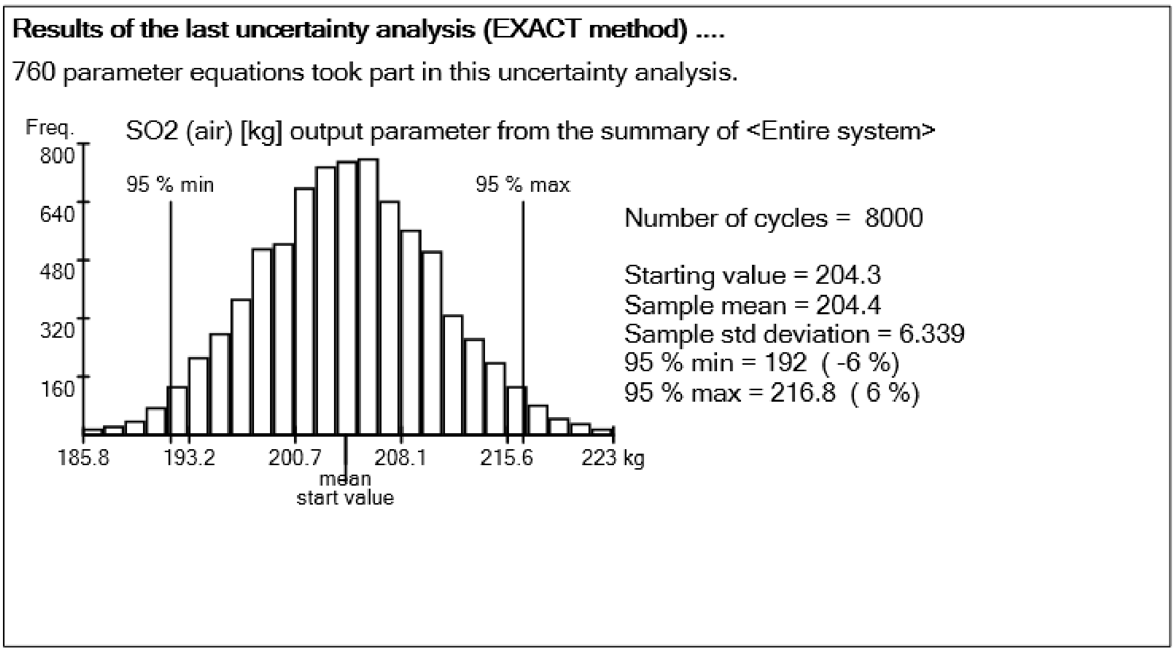

Figure 17 Estimated aleatoric uncertainty for the output variable SO_2 (air) from the system. The figure shows uncertainties based on all equations affecting the variable SO_2 (air).

8.3.2 Epistemic uncertainties

In addition to the aleatoric uncertainties, there are many different types and causes of uncertainties, which are important to analyze. These can be classified as epistemic uncertainties. However, there may also be a boundary between such uncertainties that may be important to include in an uncertainty analysis and such uncertainties that are difficult to include, or which cannot be assessed as uncertainties in the true sense, but which can behave as uncertainties in an analysis. It can thus be of value to start by identifying such uncertainties that should not be included in the uncertainty analysis. This boundary is of course not fixed but have to be assessed on a case-by-case basis. Uncertainties that may be excluded from an uncertainty analysis can, for example, be; uncertainties based on intentional errors and fraud, miscalculations and random mistakes, errors based on misconceptions or lack of knowledge or insights. Such errors occur but can be very difficult to assess.

In this study, we want to investigate different types of uncertainties that may occur to be able to increase the understanding of the characteristics and impact of these uncertainties on the model results. The following uncertainties have been selected for further analysis:

- Effects of a large random error.
- Effects of variations in the processes.
- Effects of variations in lifespan.
- Effects due to simplifications of the LCA model.
- Effects of total estimated epistemic uncertainties.

These uncertainty effects are of course just examples and for a thorough uncertainty analysis, detailed data is required and knowledge of the model's properties.

8.3.2.1 Effects of a large random error

Although not random errors in the models are a primary goal for an uncertainty analysis, it may still be of interest to analyze the effects of such an error. In this section, therefore, a random error in a significant parameter has been analyzed and the uncertainty distribution has been calculated. In this case, the parameter Crude oil has been analyzed for a random writing error in an equation in a calculation module where Crude oil accounts for about 14.4 % of the total input value of Crude oil to the model. Variations have been created within a range of ±500 % with a uniform distribution. The effects of this single error have been analyzed in a model run without variations in other parameters. The result can be found in Figure 18. As can be seen, the variations are significant
(-70 %/+67 %) but such large errors as ±500 % should be detected in an analysis of the results. For minor errors and less important parameters, the total error can be reduced to a significant extent.

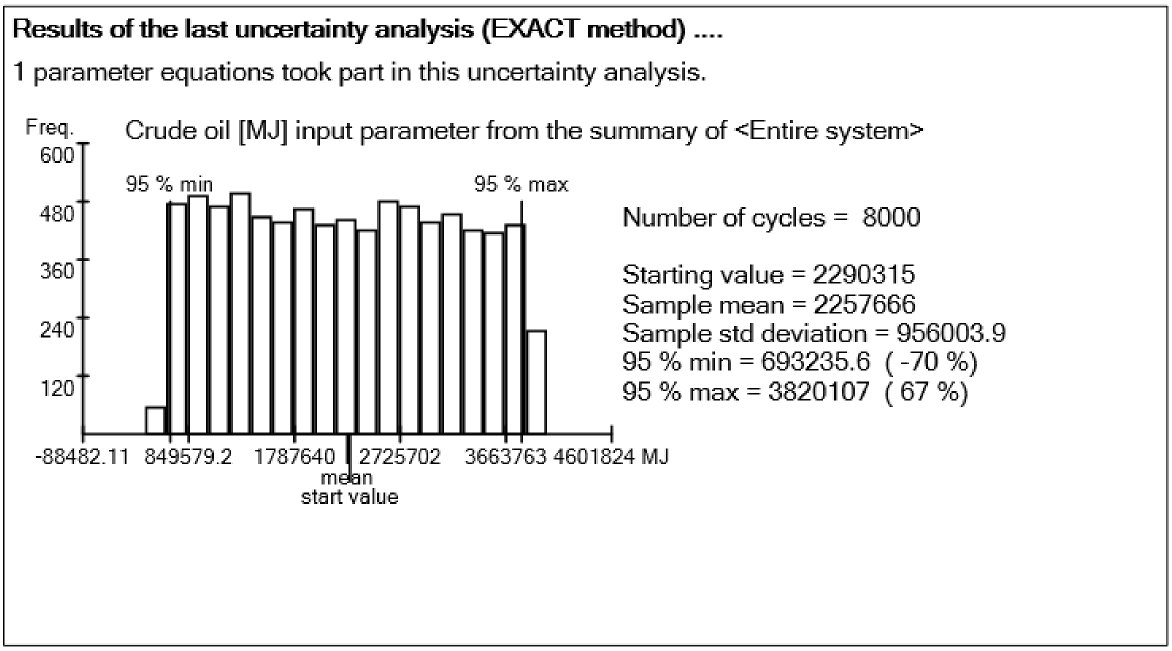

Figure 98 Model results for Crude oil with a random error in the range of ±500 % in a model/equation where crude oil contributes with about 14.4 % of the total value of Crude oil to the model. A uniform distribution of the error has been used for this type of random error.

8.3.2.2 Effects of variations in the processes

Many processes and activities are affected by considerable uncertainties or variations that are difficult to predict. It may therefore be important to consider such uncertainties and to analyze their impact on the entire system. In this example, we have chosen to analyze the excavation processes for the railway foundation. These mainly consist of excavator and dumper operations. The variations can mainly be attributed to variations in diesel consumption for the excavators or dumpers. Minor variations exist for e.g. different machine types, sizes of machines, and age distribution and maintenance of the machines. In addition, there are significant variations in driving conditions such as rain in muddy conditions, hilly terrain, the nature of the ground, the driving style of the driver (eco-driving), transport distance and driving planning, etc. These variations can have a large impact on diesel consumption and thus also on the emissions from the process. In theoretical calculations and comparisons, such variations can be standardized so that only, for the comparison, relevant variations are included. In the uncertainty calculations for this example, it has been assumed that the total variations in diesel consumption can amount to about ±40 %. The uncertainty results from the calculations are presented in Figure 19 to Figure 21. As shown from the figures, the effect on the entire results from this single change is relatively small for the Crude oil resource use, CO_2 fossil (air) emissions and emissions of NO_X (air).

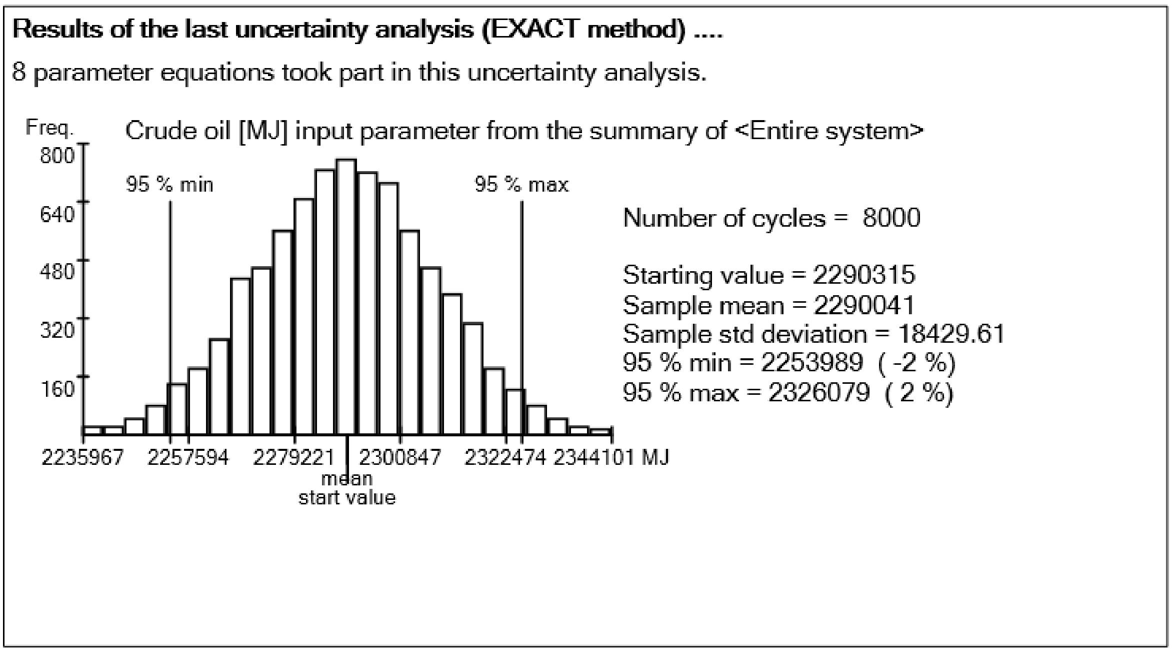

Figure 19 Estimated epistemic uncertainty for the input variable Crude oil to the system. The figure shows uncertainties based on equations for uncertainties/variations in diesel use for excavation activities (excavator and dumper operations) in the model with a variation span of ±40 %.

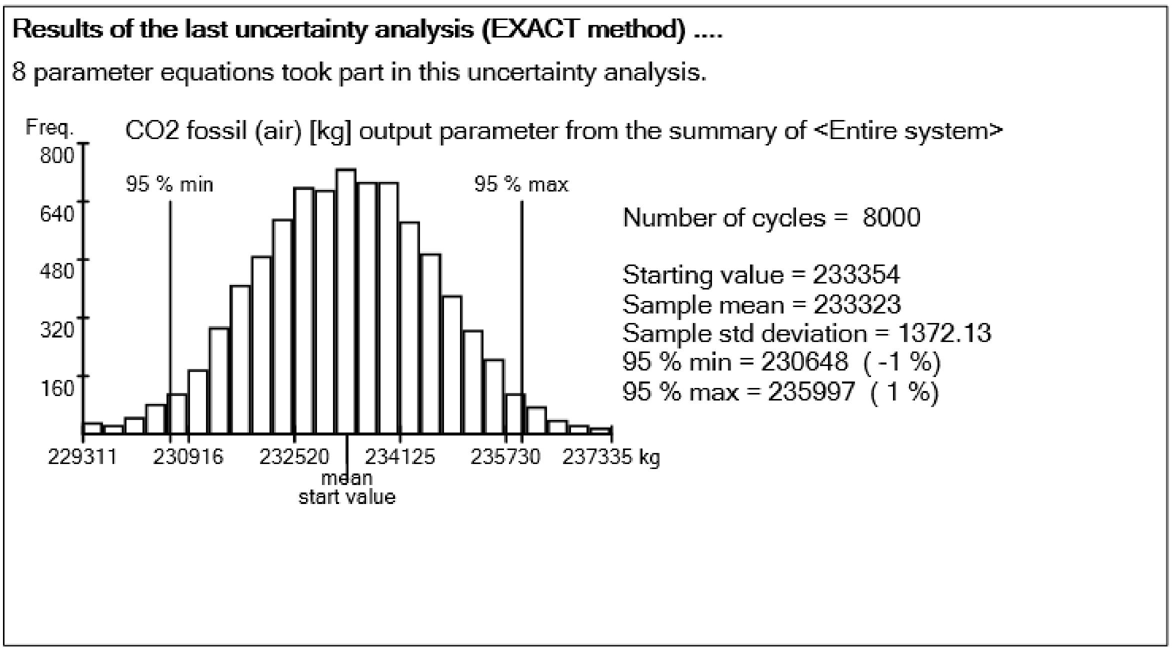

Figure 20 Estimated epistemic uncertainty for the output variable CO_2 fossil (air) from the system. The figure shows uncertainties based on equations for uncertainties/variations in diesel use for excavation activities (excavator and dumper operations) in the model with a variation span of ±40 %.

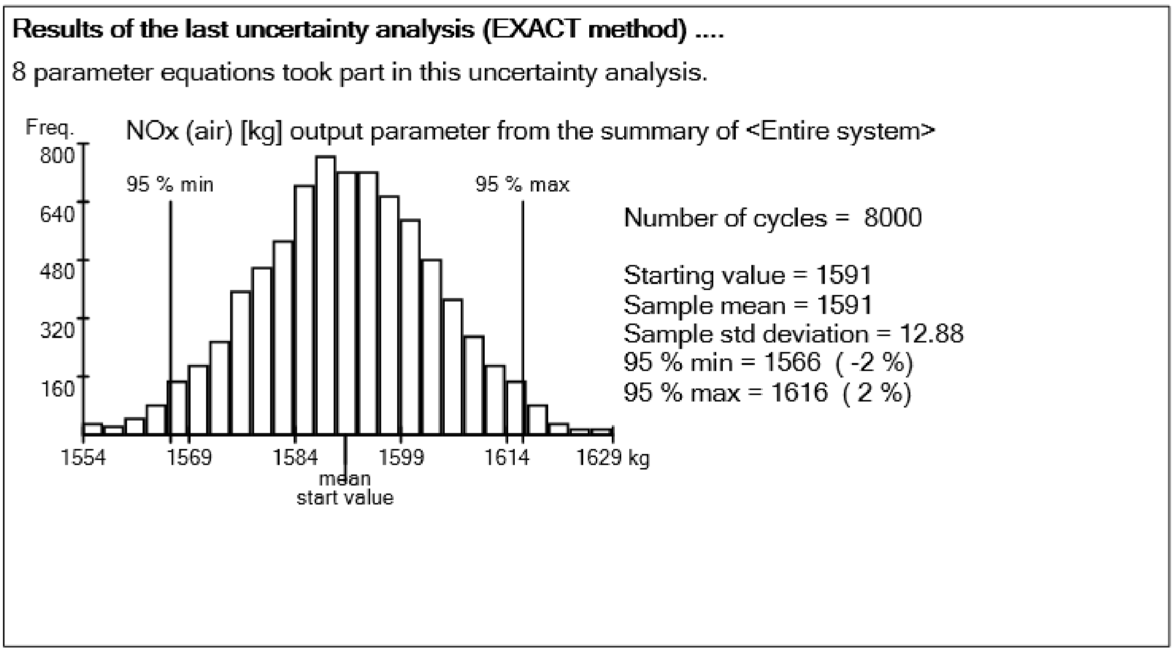

Figure 21 Estimated epistemic uncertainty for the output variable NO_X (air) from the system. The figure shows uncertainties based on equations for uncertainties/variations in diesel use for excavation activities (excavator and dumper operations) in the model with a variation span of ±40 %.

8.3.2.3 Effects of variations in lifespan

The LCA model is divided in construction, maintenance, and operation. The construction part includes the original construction of the foundation. Operation activities for foundations i.e. regular work or energy use is very rare if it exists. In the maintenance part, the foundation is repaired to its original condition due to wear during use. The wear can e.g. due to the passage of heavy trains or on external impact on the embankment. Different components in the foundation are affected differently by the wear and therefore have different lifetimes. This effect is included in the model calculations as different types of maintenance. However, the impact on the embankment can vary, for example. due to the weather and train traffic can also vary greatly, e.g. between freight traffic and passenger traffic during such a long calculation period as 60 years. This causes uncertainties in the lifetime of the different components in the foundation and thus also in the maintenance of railway foundation. The effects of these uncertainties or variations are shown in this chapter. A variation span of ±50 % for the lifetime of the components has been added to the model calculations. The results of these calculations are shown in Figure 22 to Figure 24. The results show that despite a relatively large variation span (±50 %), the impact on the entire model results is limited to well below ±10 % for the selected variables.

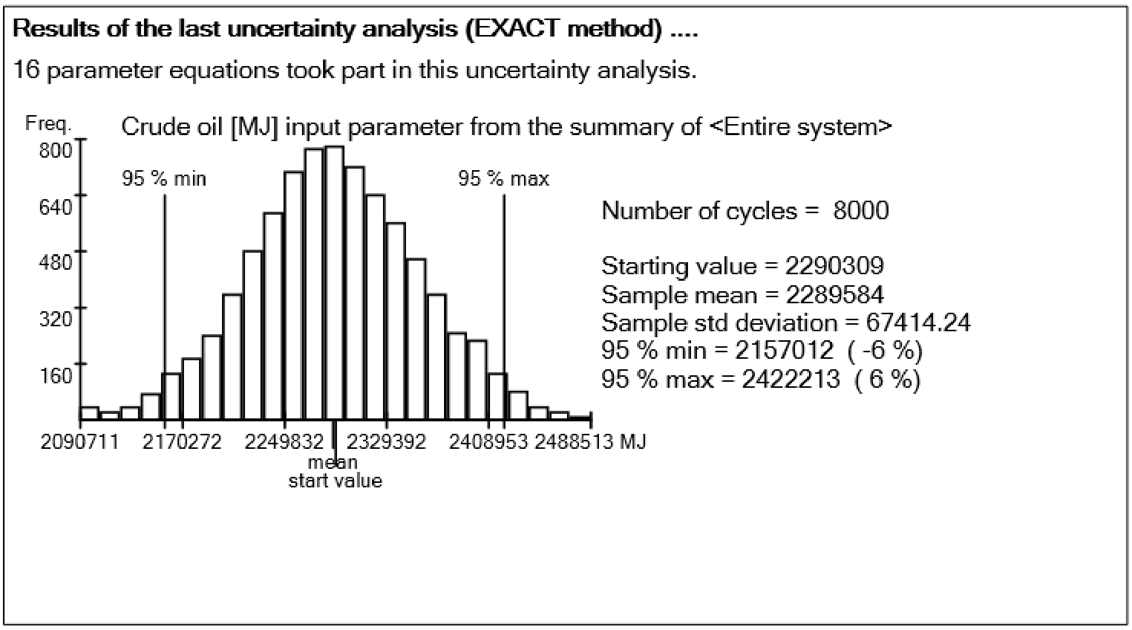

Figure 22 Estimated epistemic uncertainty for the input variable Crude oil to the system. The figure shows uncertainties based on equations for uncertainties/variations due to variations in lifespan of components in the foundation. A variation span of ±50 % for the lifetime has been used.

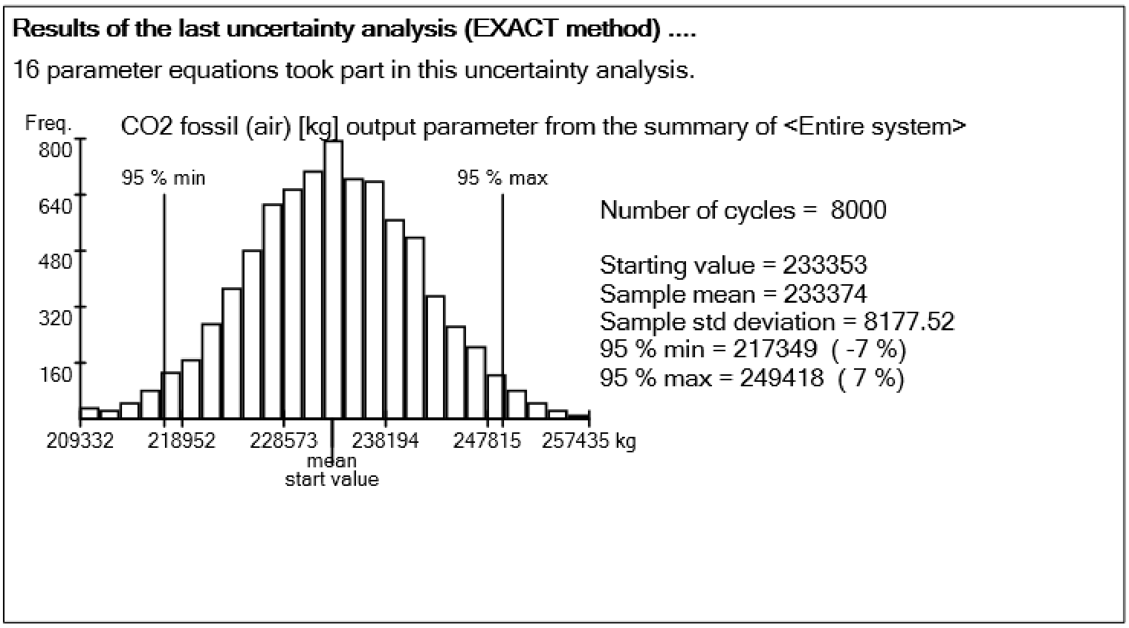

Figure 23 Estimated epistemic uncertainty for the output variable CO_2 fossil (air) from the system. The figure shows uncertainties based on equations for uncertainties/variations due to variations in lifespan of components in the foundation. A variation span of ±50 % for the lifetime has been used.

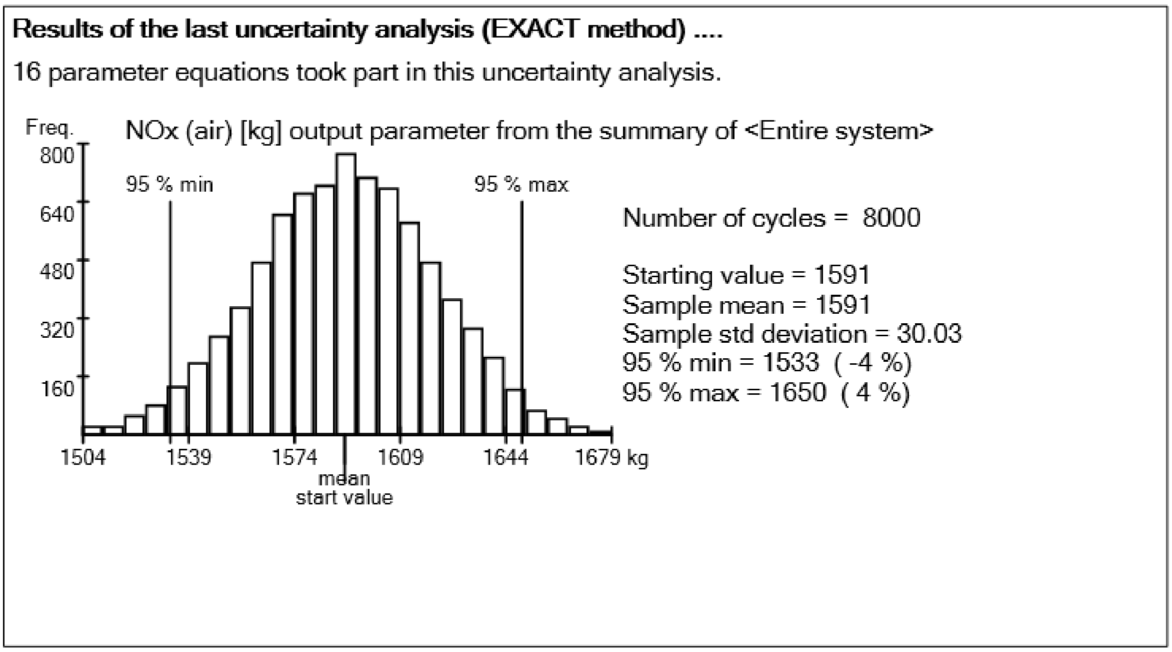

Figure 24 Estimated epistemic uncertainty for the output variable NO_X (air) from the system. The figure shows uncertainties based on equations for uncertainties/variations due to variations in lifespan of components in the foundation. A variation span of ±50 % for the lifetime has been used.

8.3.2.4 Effects due to simplifications of the LCA model

The reality that an LCA model should describe is often very complex and simplifications are often made in the models. This causes potential errors and uncertainties in the models. Sometimes, the excluded processes are known but many times there are also unknown processes, which have then been disclosed. The effects on the model results from such model simplifications are thus of great interest in the design of different models and in the estimations of uncertainties for the model results. A basic assumption when excluding different processes in an LCA model is that the contribution to a model decreases with decreasing relative size / significance for the whole model. This means that more peripheral processes in the model can be assumed primarily to be excluded, while a greater focus is on the core processes, where higher demands on uncertainties in input data are required. This chapter examines the effects of excluding certain processes in the existing LCA model for the railway foundation. The following processes have been investigated with regard to exclusion in the model:

- Geotechnical survey, track foundation
- Forest felling
- Construction of service roads
- Rock bolting reinforcement
- Application of protecting wire netting for rock
- Geotextile application
- Protection and wildlife fences
- Cable channels with lid
- Foundations for overhead contact line poles
- Stay anchorage
- Beam for noise protection
- Establish construction site

- General energy use for construction site

In the analysis, an uncertainty range of -100 % to 0 % has been added to each of the processes to be analyzed for exclusion. A simultaneous Monte Carlo simulation of the processes in the model within the range and with a uniform distribution of the values has been made. This results in a total distribution of the results for each variable. In Figure 25 to Figure 27 the results are presented for the variables Crude oil, CO_2 fossil (air) and NO_X (air). In the figures, Starting value represents the original mean value without applied variations. Sample mean is the mean value when all variations are applied, and the left edge of the distribution represents a situation where almost all processes for exclusion have the value zero simultaneously i.e. are excluded in the model. As shown in Figure 25, the consumption of crude oil is reduced from about 2290309 MJ to about 1234770 MJ, i.e. by 46 %. The corresponding reduction for CO_2 fossil (air) is 43 % and for NO_X (air) 46 %.

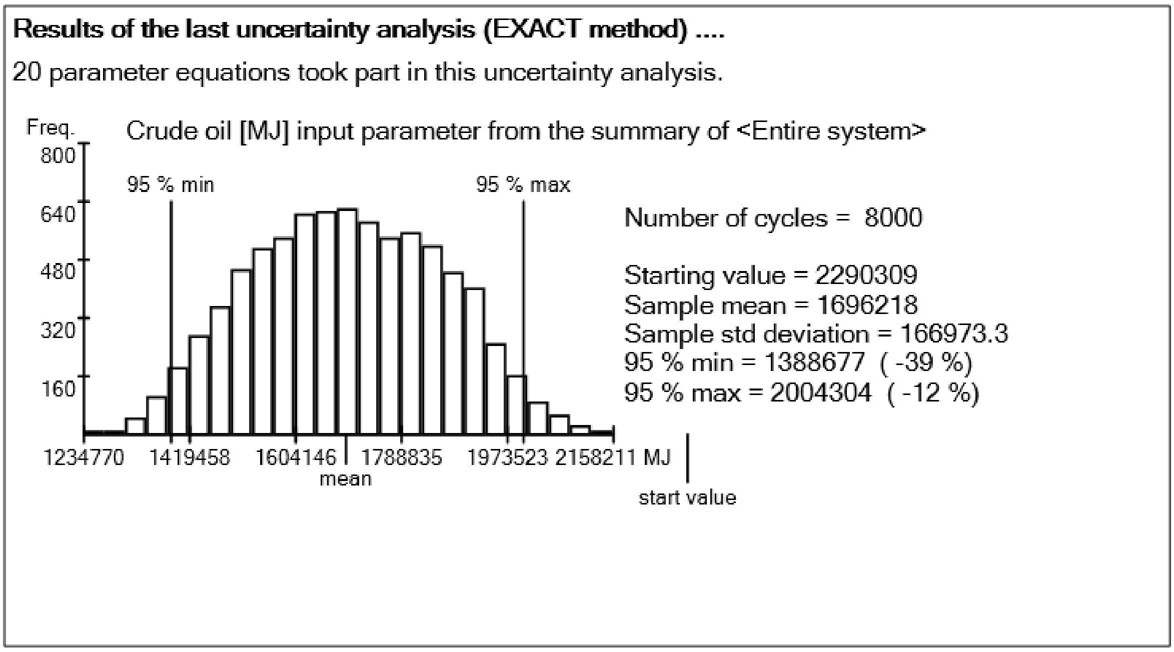

Figure 25 Estimated epistemic uncertainty for the input variable Crude oil to the system. The figure shows uncertainties due to the exclusion of certain selected processes in the LCA model. A variation span of
-100 % to 0 % for each process selected for exclusion has been used. The figure will thus show the stochastic distribution of using each process to a certain degree at the same time.

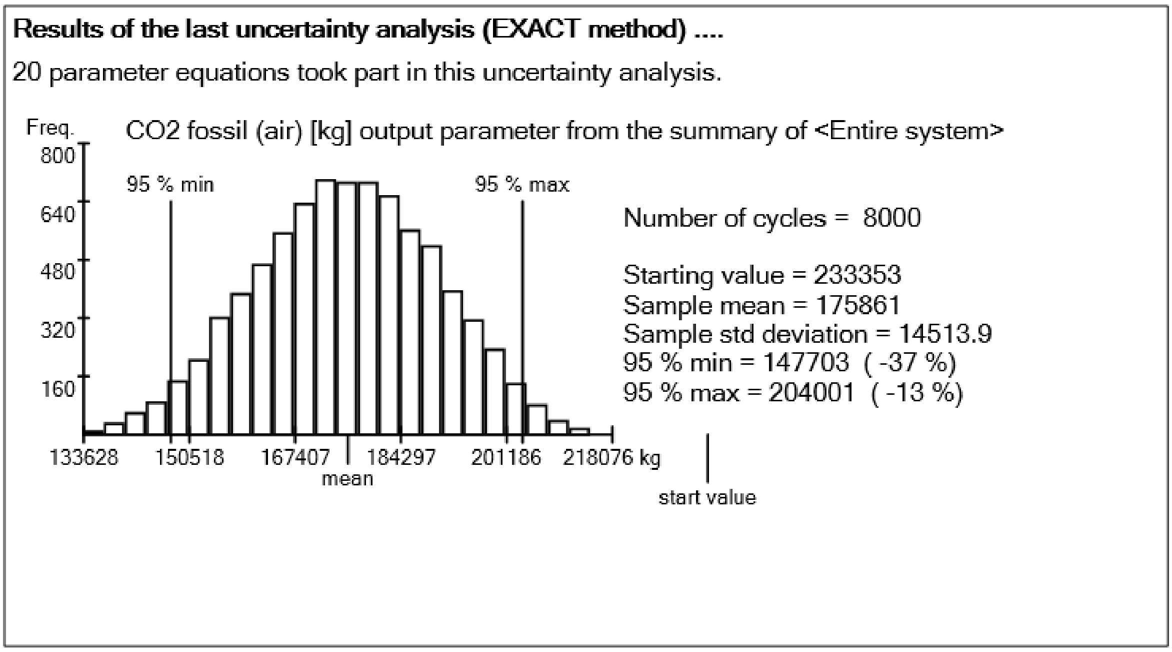

Figure 26 Estimated epistemic uncertainty for the output variable CO_2 fossil (air) from the system. The figure shows uncertainties due to the exclusion of certain selected processes in the LCA model. A variation span of -100 % to 0 % for each process selected for exclusion has been used. The figure will thus show the stochastic distribution of using each process to a certain degree at the same time.

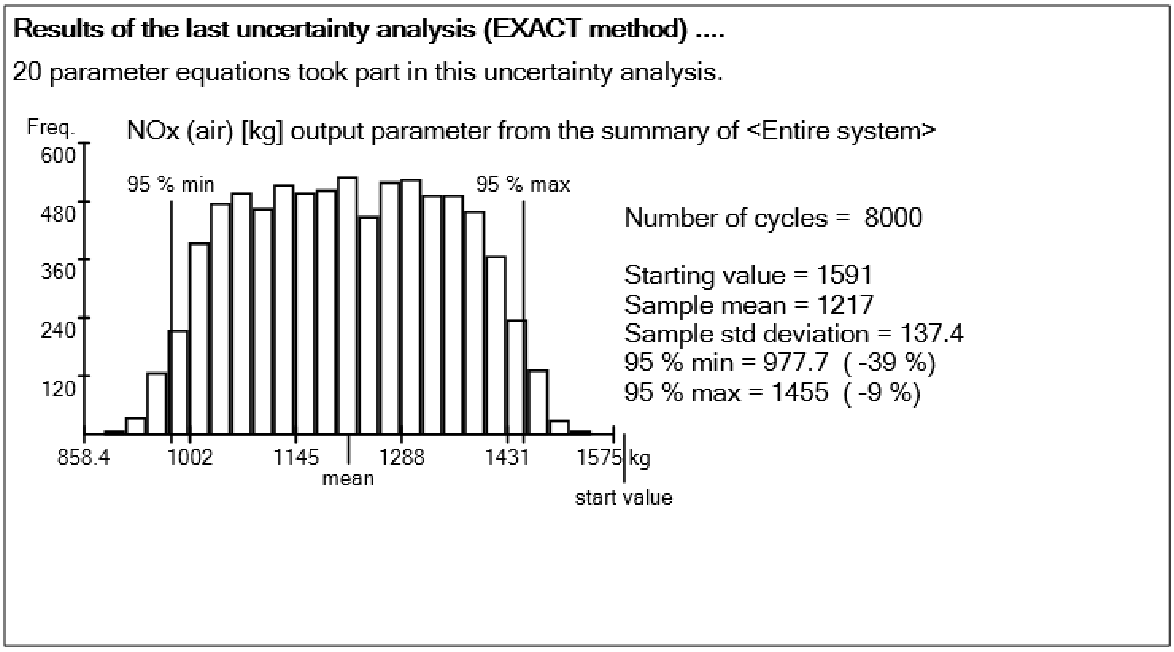

Figure 27 Estimated epistemic uncertainty for the output variable NO_X (air) from the system. The figure shows uncertainties due to the exclusion of certain selected processes in the LCA model. A variation span of -100 % to 0 % for each process selected for exclusion has been used. The figure will thus show the stochastic distribution of using each process to a certain degree at the same time.

8.3.2.5 Effects of total estimated epistemic uncertainties

So far, some specific uncertainties have been analyzed in a context of the entire LCA model. However, it is the overall uncertainty from the entire model parts that will determine the uncertainty for the individual model results. In order to make such an overall analysis, uncertainty for all or at least the most important data must be developed. Producing reliable uncertainty data for all inventory data in an LCA model is a very large and difficult work, which requires a lot of time and a good methodology for producing such data. Within the framework of this project, it has not been possible to produce "real" uncertainty data based on actual measurements. However, estimates of uncertainties have been made based on experiences from data collection within LCA, uncertainties in various types of measurements, and the concept of classifying uncertainty data into different types of uncertainties. Basic uncertainty data for the different parts of the LCA model have thus been estimated and implemented in the computer model. The used uncertainty data for the model can be found in Table 4. The entire model results for the variables; Crude oil, CO_2 fossil (air), NO_X (air), and SO_2 (air) have been calculated and the uncertainty has been analyzed. The results are presented in Figure 28 to Figure 31. As shown from the figures, the overall uncertainty distribution for the analyzed variables is relatively narrow and the equation system seems to be relatively robust and stable against variations in used model data.

Table 20 Estimated uncertainty data for the entire LCA model of the railway foundation.

Parameter	Used epistemic uncertainties	Type of uncertainties
Energy input		
Crude oil	±10 %	Measurement and process variations
Emissions		
CO_2	±3 %	Measurement
NO_X	±3 %	Measurement
SO_2	±7 %	Measurement
Lifetime	±30 %	Variations in lifetime for construction components
Processes	±5 % to ±20 %	Variations in flow to the main modules Construction and Maintenance

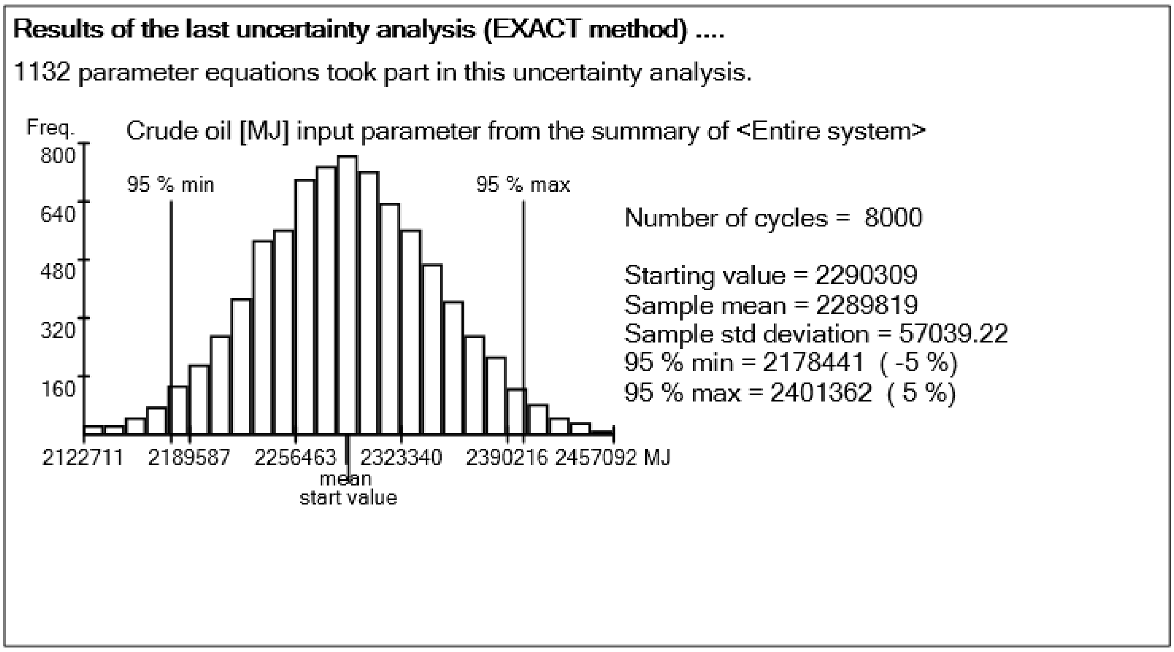

Figure 108 Estimated epistemic and aleatoric uncertainties for the input variable SO_2 (air) from the entire system. The figure shows the total uncertainty from the main processes in the LCA model.

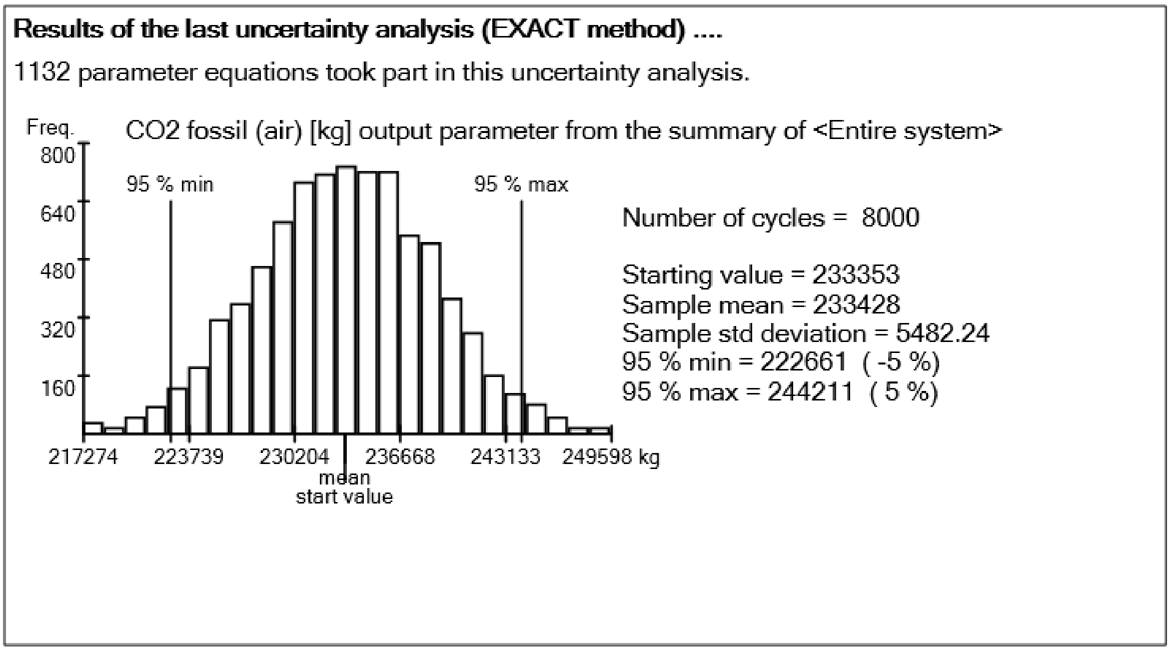

Figure 119 Estimated epistemic and aleatoric uncertainties for the output variable CO_2 fossil (air) from the entire system. The figure shows the total uncertainty from the main processes in the LCA model.

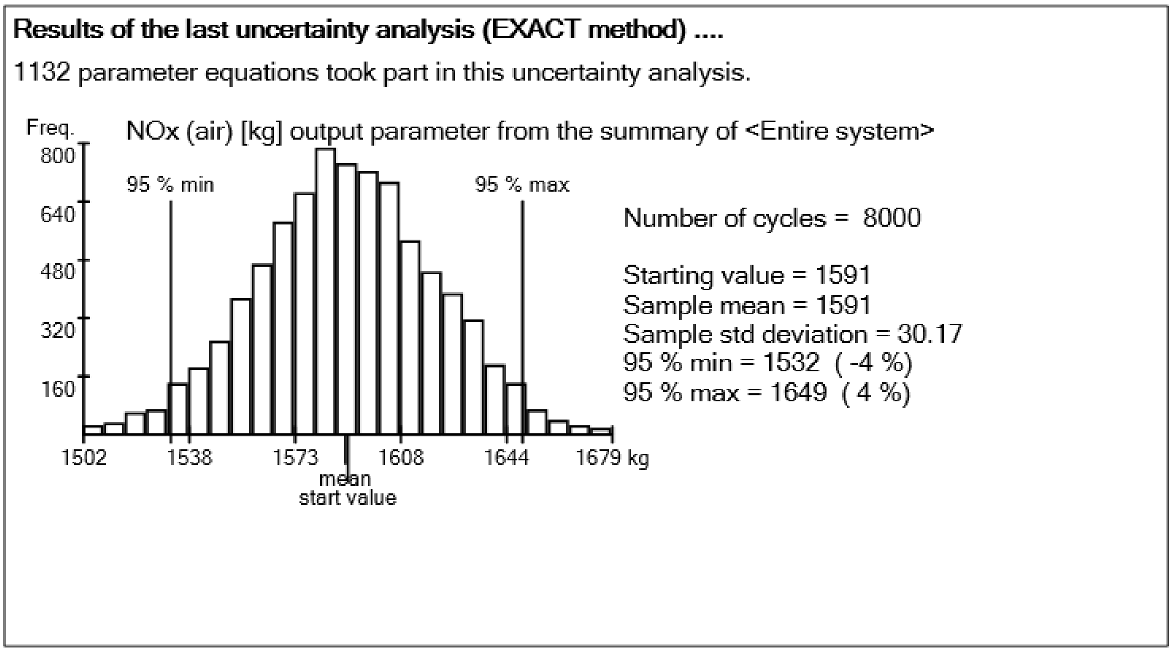

Figure 30 Estimated epistemic and aleatoric uncertainties for the output variable NO_X (air) from the entire system. The figure shows the total uncertainty from the main processes in the LCA model.

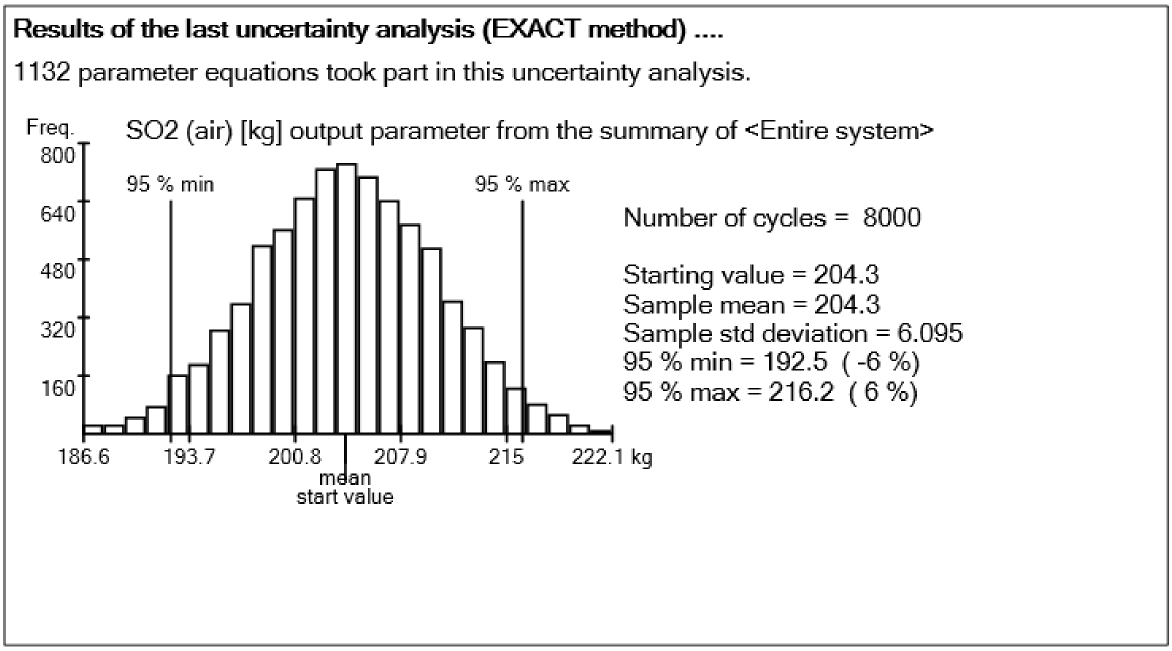

Figure 31 Estimated epistemic and aleatoric uncertainties for the output variable SO_2 (air) from the entire system. The figure shows the total uncertainty from the main processes in the LCA model.

9 Discussion and conclusions

In this report, an attempt has been made to categorize uncertainties and to find a methodology suitable for identifying uncertainty sources and levels using this categorization. The main findings presented in this report are:

- There are many different types of uncertainties related to LCA and to environmental impacts in general. It is possible to categorize them to be able to have a better understanding of the uncertainties and to identify the sources.
- Many uncertainties related to LCA can be reduced or eliminated by regulation or by setting well defined system boundaries. Not all uncertainties can be treated this way however, which has been previously done in several regulations for data quality. There will always be a physical variation that is difficult to reduce. The efforts should instead be aimed at reducing or controlling other types of variations.
- There is a lack of validated input data including uncertainty factors for LCA-applications, this is the major obstacle for implementing probabilistic methods in LCA.
- It is possible to incorporate uncertainties into almost any LCA-tool using Monte Carlo simulation, since todays computers have sufficient capacity. However, it may be more important to focus on reducing the effects of system boundaries and user choices, since they usually have a larger impact on the results than the physical variations in a parameter.
- The current practice of including uncertainties using different methods for emission factors is not sufficient for estimating uncertainty. The effect of variations in material amounts and estimated service life for each input parameter will have a large influence on the results, which is often not included in today's methods that are more focused on data quality for the emission factors themselves.
- In the presented case study, the concrete emissions had the largest impact due to larger amounts and higher total emissions. A reduction in concrete amounts, emissions and/or increase in expected service life will therefore reduce the total yearly impact of this kind of structure.
- The effect of uncertainties on LCA depends on the purpose of the LCA, what it is supposed to be used for. The ultimate uncertainty in a parameter can be quite large, it is not certain, however, that all sources to this uncertainty level are relevant for all purposes. Depending on the use of the LCA, several uncertainty sources may be removed/reduced depending on the situation.
- With the large variations shown in this report related to LCA, uncertainties must be taken into account as a basis for decisions when comparing different solutions. This includes, for example, the function and durability of the structures during their service life, where this needs to be well-documented in a technologically sound and equivalent manner. If uncertainties are not considered, it is recommended that the LCA results are not used as a basis for procurement decisions.

One of the main reasons for the difficulty of integrating uncertainties in LCA is the actual definition: what is an uncertainty? There are many uncertain aspects affecting the result of an LCA, all of them cannot however be defined as actual uncertainties. As stated above, the effect of uncertainties is very difficult to quantify since the definitions and sources may vary. Major influence on the environmental impact of e.g. a bridge is given by the choices and limitations set by the client. One such example is a bridge that is supposed to span a certain distance with a certain load. After the procurement phase, a certain solution from a company is chosen as the best one, where different aspects have been considered including environmental effects. In the preproduction phase, the client then changes the limitation so that the bridge has to be slightly redesigned, leading to larger environmental impact. In such a case, it is possible that the final impact is larger than the worst case from the original situation, leading to a very large variation. But is this an uncertainty? It could be argued that such a variation is not an uncertainty that should be included in LCA even though it has a large impact on the final result, since the purpose of the LCA in this case was to compare different solutions for a certain set of constraints and limitations. It raises the question however, if the original limitations were relevant?

This example specifies one difficulty of addressing uncertainty in LCA, since in such a case, the variation in a parameter may have a low impact on the result compared to the described change in the limitations. Therefore, it is of great importance to focus on the system boundaries and limitations for each LCA application, if the purpose is to use LCA as a tool for decision support. Otherwise, the decisions may be based on irrelevant numbers leading to poor solutions for reducing environmental impact.

The impact of uncertainties is different depending on what the LCA should be used for. It is not reasonable to believe e.g. that there are as many uncertainties for a single construction material as for an entire bridge, since the first is associated with fewer possible variations. There are also differences in knowledge about different stages, e.g. more knowledge about emissions in the construction phase than in the user phase. Including uncertainties in a LCA is very useful for improving a specific solution, a structural component or the entire structural design, since it is then possible to find the most influential parts of the process and efforts can be taken to reduce these uncertainties.

Comparing different solutions, however, require a large confidence in both input and output parameters, the applied LCA-models and the users themselves who execute the calculations. As was shown in the state-of-art (Section 5.1), previous studies have shown that the variability between different LCAs are large depending on system boundaries and chosen input data. With today’s knowledge about the uncertainties, it is not possible to make comparisons without breaking down the influencing processes and categorizing the uncertainties.

10 Future work

The potential for future work regarding consideration of uncertainties in LCA is large. Several important aspects regarding uncertainties are still not studied or need further attention. Based on the findings in this report, the following areas should be prioritized:

- The main focus should be regarding collection of LCI-data and associated uncertainty parameters, since this is an important aspect for the possibility of incorporating uncertainties in LCA-calculations. Today, uncertainty data is usually missing for both collected data and complete LCA datasets. Both development of uncertainty data for new LCA datasets and assessment and approximation of uncertainty data for existing data may be required. The methodology for collecting and estimating uncertainty presented here can be further developed and tested on real processes and objects. The collection of data should be regulated within present systems such as EPD, since this will lead to a faster implementation.
- When data have been collected for enough processes, the next step can be to fully implement probabilistic methods in LCA-tools where this is needed. If an LCA is supposed to be used for procurement, including uncertainties is necessary for the transparency of the results presented and compared for different solutions.

The project team behind this report is currently involved in a small pilot study for collecting LCI-data using the proposed methodology. When this is finished, the results will be connected to this report.

11 References

Baker J.W. and Lepech M., 2009, Treatment of Uncertainties in Life Cycle Assessment, Proc. of the 10th Int. Conf. on Struct. Safety and Reliability, Osaka, Japan. Sep. 13-17

Batouli M, Bienvenu M, Mostafavi A, 2017, Putting sustainability theory into roadway design practice: Implementation of LCA and LCCA analysis for pavements type selection in real world decision making, Transportation Research Part D, Vol 50, pp 289-302

Basson L, Petrie J.G, 2007, An integrated approach for the consideration of uncertainty in decision making supported by Life Cycle Assessment, Environmental Modelling & Software, Vol 22 pp 167-176

Benjamin J.R. and Cornell C.A., 2016, Probability, statistics and decision for civil engineers, Dover publications inc., Mineola, New York, USA

Berendsen H.J.C, 2011, A Student's Guide to Data and Error Analysis, Cambridge University Press, Cambridge

Bisinella V, Conradsen K, Christensen T.H, 2016, A global approach for sparse representation of uncertainty in Life Cycle Assessments of waste management systems, Int. J Life Cycle Assess

Björklund A.E., 2002, Survey of Approaches to Improve Reliability in LCA. The Int. Journal of Life Cycle Assessment, 3(7):64-72.

Blom G., 1989, Sannolikhetsteori och statistikteori med tillämpningar, Studentlitteratur, Lund, Sweden

Cacuci D.G., 2003, Sensitivity and uncertainty analysis, Chapman & Hall/CRC, Boca Raton, USA

Chakhunashvili A., Johansson P., Bergman, B., 2004, Variation Mode and Effect Analysis. Proceedings of the Annual Reliability and Maintainability Symposium, 364 – 369.

Clavreul J, Guyonnet D, Christensen T.H., 2012, Quantifying uncertainty in LCA-modelling of waste management systems, Waste Management, Vol 32, pp 2482-2495

Cucurachi S, Borgonovo E, Heijungs R, 2016, A protocol for the global sensitivity analysis of impact assessment models in life cycle assessment, Risk Analysis, Vol 36, pp 357-377

Ditlevsen O. and Madsen H., 1996, Structural Reliability Methods. John Wiley & Sons.

Deming, W.E., 1986, Out of the crisis. MIT-CAES, Cambridge, MA.

Elms D.G., 1985, The principle of consistent crudeness, in C. B. Brown, J-L. Chameau, R. Palmer and J. T. P. Yao (Eds.), Proceedings of NSF Workshop on Civil Engineering Applications of Fuzzy Sets, Purdue Univ. Sch. of Civil Engineering, 35–44.

EPD, 2015, General programme instructions for the international EPD® system, http://www.environdec.com/sv/

Geisler G., Hellweg S., Hungerbühler K., 2005, Uncertqainty analysis in life cycle assessment (LCA): case study on plant-protection products and implications for decision making, Int. Journal of LCA, Vol 10, No 3, pp 184-192

Groen E.A, Heijungs R, Bokkers E.A.M, de Boer I.J.M, 2014, Methods for uncertainty propagation in life cycle assessment, Environmental Modelling &Software, Vol 62, pp 316-325

Guo M, Murphy R.J., 2012, LCA data quality: Sensitivity and uncertainty analysis, Science of the total environment, Vol 435-436, pp 230-243

Hoxha E., Habert G., Lasvaux S., Chevalier J., Le Roy R., 2017, Influence of construction material uncertainties on residential building LCA reliability, Journal of Cleaner Production, Vol 144, pp 33-47

Huijbregts M.A.J., 1998a, Application of Uncertainty and Variability in LCA Part I: A General Framework for the Analysis of Uncertainty and Variability in Life Cycle Assessment. Int Jour. of Life Cycle Assess., 3(5):273-80.

Huijbregts M.A.J., 1998b, Application of Uncertainty and Variability in LCA Part II: Dealing with Parameter Uncertainty and Uncertainty Due to Choices in Life Cycle Assessment. Int. Jour. of Life Cycle Assess., 3(6):43-51

ILCD, 2010a, European Commission - Joint Research Centre - Institute for Environment and Sustainability: International Reference Life Cycle Data System (ILCD) Handbook – General guide for Life Cycle Assessment - Detailed guidance. First edition. EUR 24708 EN. Luxembourg. Publications Office of the European Union

ILCD, 2010b, European Commission - Joint Research Centre - Institute for Environment and Sustainability: International Reference Life Cycle Data System (ILCD) Handbook - Specific guide for Life Cycle Inventory data sets. First edition. EUR 24709 EN. Luxembourg. Publications Office of the European Union

ISO 14040:2006. Environmental management: Life cycle assessment: Principles and framework, ISO, Geneva, 2006.

ISO 14044:2006. Environmental management: Life cycle assessment: Requirements and guidelines, ISO, Geneva, 2006.

Johansson P., Chakhunashvili A., Barone S., Bergman, B., 2006, Variation Mode and Effect Analysis: a Practical Tool for Quality Improvement. Quality and Reliability Engineering International, 22: 865 - 876.

Johannesson, P., Bergman, B., Svensson, T., Arvidsson, M., Lönnqvist, Å., Barone, S. och de Maré, J. A 2013, Robustness Approach to Reliability. Quality and Reliability Engineering Int., 29(1): 17–32.

Kennedy M.C, O´Hagan A, 2001, Bayesian calibration of computer models, Journal of Royal Statistics Society, Vol. 63, pp 425-464

Kroese D.P, Taimre T., and Botev Z.I., 2011, Handbook of Monte Carlo methods, John Wiley, e-book.

Lacirignola M, Blanc P, Girard R, Pérez-Lopez P, Blanc I, 2017, LCA of emerging technologies: addressing high uncertainty on inputs' variability when performing global sensitivity analysis, Science of the Total Environment, Vol 578, pp 268-280

Lasvaux S., Habert G, Peuportier B., Chevalier J., 2015, Comparison of generic and product-specific Life Cycle Assessment databases: application to construction materials used in building LCA studies, Int J Life Cycle Assess, 20: 1473-1490.

Liljenström C., 2013, Life Cycle Assessment in Early – Planning of Road Infrastructure: Application of The LICCER-model, Master Thesis, KTH, Stockholm.

Liu K., Liu F-R., Chiu S-Y., Hung M-J., and Kuo J-Y., 2013, The Propagation of Probabilistic and Possibilistic Uncertainty in a Life Cycle Assessment: A Case Study of a Naphtha Cracking Plant in Taiwan, Int. Jour. of Env. Science and Developm., 4(6): 652-657.

Lloyd S.M, Ries R, 2007, Characterizing, Propagating, and Analyzing Uncertainty in Life-Cycle Assessment – A survey of quantitative approaches, Journal of Industrial Ecology, Vol 11, pp 161-179

Lo S-C., Ma H-W, and Lo S-L., 2005, Quantifying and Reducing Uncertainty in Life Cycle Assessment Using the Bayesian Monte Carlo Method, Science of The Total Environment, 340(1–3): 23-33.

Mackenzie S., Leinonen I., Ferguson N., Kyriazakis I., 2014, Accounting for uncertainty in the quantification of the environmental impacts of Canadian pig farming systems, Proceedings of the 9th Int. Conference on Life Cycle Assessment in the Agri-Food Sector, San Francisco, pp 743-751.

Mathworks, 2017, Matlab release 2017a

Melchers R.E., 1999, Structural reliability analysis and prediction, John Wiley, Chichester, New York

Miliutenko S., 2012, Life Cycle Impacts of Road Infrastructure: Assessment of energy use and greenhouse gas emissions, Licentiate Thesis, KTH, Stockholm

Nowak A. S. and Collins K. R., 2000, Reliability of Structures. McGraw-Hill.

Olivetti E, Patanavanich S, Kirchain R, 2013, Exploring the viability of probabilistic under-specification to streamline life cycle assessment, Environmental Science and Technology, Vol 47, pp 5208-5216.

Patanavanich S, 2009, Exploring the viability of probabilistic under-specification as a viable streamlining method for LCA, Bachelor Thesis, MIT

Shewhart, W. A., 1931, Economic Control of Quality of Manufactured Product. Van Nostrand, New York.

SimaPro, 2018, SimaPro 8.5, PRé Sustainability, https://simapro.com/

Stewart M. and Melchers R.E., 1997, Probabilistic Risk Assessment of Engineering Systems. Chapman & Hall, London.

Stripple H., Life Cycle Assessment of Road - A Pilot Study for Inventory Analysis, second revised edition., IVL report B1210E, (2001).

Stripple H., Uppenberg S., 2010, Life cycle assessment of railways and rail transports - Application in environmental product declarations (EPDs) for the Bothnia Line. IVL-rapport B1943.

Säynäjoki A, Heinonen J, Junnila S, Horvath A, 2017, Can life-cycle assessment produce reliable policy guidelines in the building sector?, Environmental Research Letters, 12-2017

Tecchio P., 2015, Streamlining life cycle assessment to support Ecodesign through multi-criteria materials selection, PhD-Thesis, Politecnico di Torino.

Thinkstep, 2018, GaBi ts 8.6, http://www.gabi-software.com

Toller S., Norberg J., 2017, Klimatkalkyl version 5.0 - Beräkning av infrastrukturens klimatpåverkan och energianvändning i ett livscykelperspektiv, Trafikverket.

Toller S., Tokate M., Nyholm S., 2015, Klimatkalkyl version 3.0 - Beräkning av infrastrukturens klimatpåverkan och energanvändning i ett livscykelperspektiv, Trafikverket.

Trafikverket, 2017, TDOK 2015:0480 Klimatkrav i planläggning, byggskede, underhåll och på teknisk godkänt järnvägsmateriel

Vick S.G., 2002, Degrees of Belief: Subjective Probability and Engineering Judgement. Virginia: ASCE Press

VTT, 2018, SULCA - Sustainability tool for Ecodesign, Footprints & LCA, VTT, Finland

Wei W., Larrey-Lassalle P., Faure T., Dumoulin N., Roux P., Mathias, J.-D., 2016, Using the Reliability Theory for Assessing the Decision Confidence Probability for Comparative Life Cycle Assessments, Environmental Science & Technology. American Chemical Society, 50(5), pp. 2272–2280.

Weidema B.P., Bauer C., Hischier R., Mutel C., Nemecek T., Reinhard J., Vadenbo C.O., Wernet G., 2013, Overview and methodology. Data quality guideline for the ecoinvent database version 3. Ecoinvent Report 1(v3). St. Gallen: The ecoinvent Centre.

Yu B., Liu Q., Gu X., 2017, Data quality and uncertainty assessment methodology for pavement LCA, International Journal of Pavement Engineering.

Zhang Y.-R., Wu W.-J., Wang Y.-F., 2016, Bridge life cycle assessment with data uncertainty, Int. Journal of Life Cycle Assessment.

Appendix A – Basic statistical concepts

A.1 General equations

From a statistical point of view, it is important to make some distinctions when performing analysis or measurements. For a stochastic variable X, the entire population (x_1, x_2, $x_3 \ldots x_n$) includes all the values that exist and can be measured. Usually, it is the entire population that is of interest to investigate. However, in many practical situations, it is not possible to investigate the entire population. Instead, a sample of the entire population has to be used to estimate the values for the entire population. The mean value of the entire population is usually denoted μ, defined as the sum of each value in the population multiplied with its probability to occur (Eq. A.1), while the mean value of the sample is denoted $\bar{x}$, defined as the sum of the sample values divided by the number of samples (Eq. A.2).

$\mu = \sum xP(x)$	Mean	(A.1)
$\bar{x} = \frac{x_1+x_2+x_3+\ldots+x_n}{n}$	Sample mean	(A.2)

The traditional method for the determination of the uncertainty of a parameter is to perform many (or at least several) measurements of the parameter (X) during normal conditions and then calculating the average deviation or the standard deviation (s), Eq. A.6, of the sample. The arithmetic average ($\bar{x}$) of n different measurement samples is calculated. For the average deviation, Eq. A.5, the absolute value of the differences between the measurement values and the average value are calculated. The average value of these differences is called the average deviation and can be used as a measure of the uncertainty. A more common way to express the deviation is by the standard deviation where the sum of the squares of the differences is used as a base for the measure of the variations. For a sample, the sum is divided by (n-1) measurements to achieve the variance (s^2) and the standard deviation (s) is the square root of the variance. The standard deviation of the entire population is usually denoted σ, see Eq. A.3, while the standard deviation of a sample is denoted s, see Eq. A.6. The variance itself is expressed with Eq. A.4 The division with (n-1) is called the Bessel correction and used for improving the sample estimate. The average deviation and the sample standard deviation both give a measure of the variations in the same unit as the measured variable but the values are slightly different.

$\sigma = \sqrt{E[(X-\mu)^2]}$	Standard deviation	(A.3)
$\sigma^2 = E[(X-\mu)^2]$	Variance	(A.4)
$\frac{\sum_n^1 \lvert X_n-\bar{X} \rvert}{n}$	Average deviation	(A.5)
$s = \sqrt{\frac{\sum_n^1 (X_n-\bar{X})^2}{(n-1)}}$	Sample standard deviation	(A.6)

Where E(X) is the expected value.

According to the law of large numbers large random samples are almost always representative of the population.

Another common way of describing the variation in a variable is by the use of coefficient of variation, often denoted cov, CoV, CV or V. This is the standardized measure of dispersion of a probability distribution and is the ratio of the standard deviation to the mean as expressed in Eq. A.7.

$$CV = \frac{\sigma}{\mu} \qquad \text{Coefficient of variation for a population} \qquad (A.7)$$

This relation shows the extent of the variability in relation to the mean, which is often easier to grasp than just the standard deviation. It can be expressed as a percentage or with a number between 0 and 1, with a low CV representing a low variability in the population. There are also other representations that can be used to describe uncertainty and variation, e.g. use of intervals with a maximum and minimum value and other combination.

For most variables, there is an error in the estimations of the mean and standard deviation since they are based on sample values. As the mean value of the sample ($\bar{x}$) approximates the mean value for the entire population (μ), the sample mean value can vary between different sample measurements. The error in the sample mean depends on the amount of observations (measurements) and is called standard error of the mean (SEM) and represents the standard deviation of the error in the sample mean compared to the true mean (μ). The SEM value is usually calculated by the standard deviation of the sample. The SEM value can be calculated by dividing the sample standard deviation (s) with the square root of the number of observations (measurements), n as below in Eq. A.8.

$$SEM = \frac{s}{\sqrt{n}} \qquad \text{standard error of the mean} \qquad (A.8)$$

When data is measured both from a mean and an uncertainty perspective, the results are reported as the mean value and uncertainty span. If the standard deviation is used for the uncertainty, the value can be presented as the $\bar{x} \pm s$. An uncertainty can also be presented as an absolute error or a relative error. The presentation above shows an example of an absolute error where the uncertainty interval has the same unit as the measured value. The relative error is the absolute error divided by the measured value such as $\Delta X/\bar{X}$. Usually, the relative error is presented as a percentage error in which the relative error is multiplied by 100. It is thus easy to convert between an absolute error and a percentage error.

A.2 Distributions

For most physical parameters, it is logical to describe a random variable with some sort of continuous distribution. A continuous random variable can take any value with a certain probability, with statistical descriptions for the most expected value and the variability depending on the type of distribution.

One of the most common distributions used in statistics and probability application is the normal, or Gaussian, distribution. It is represented by its mean and standard deviation as shown in A.1, with this example being the standard normal distribution ($\mu=0$, $\sigma=1$). The shape of this distribution has also provided it with its other name, the bell curve. Many physical phenomena can be described by a normal distribution, and since it is a naturally common distribution, it is also suitable to use for parameters of which the distribution is unknown (Blom 1989). This makes the normal distribution very useful for statistical applications and for describing the uncertainty of a variable. Furthermore, according to the central limit theorem for the addition of a large number of independent variables the sampling mean will be Gaussian. Thus, if the sum of many independent random variables is calculated, each of which makes some, but not necessarily equal contribution to the outcome, the result is expected to be Gaussian. It should also be noted that the result from multiplication of Gaussian random variables approaches a log-normal distribution according to the same central limit theorem, this multiplicative version is also sometimes called Gibrat's law.

If a normal distribution is assumed, the standard deviation means that the average value has a certain probability to be in a specific range. These ranges are shown in Figure A.1. The value range is presented within ± 1 standard deviation. As shown in the figure, the probability for the value X to be in that range is 68.2 %. The probability for the value to be in the range of $\mu\pm2\sigma$ is 95.4 % and the probability for the corresponding $\mu\pm3\sigma$ is 99.7 %.

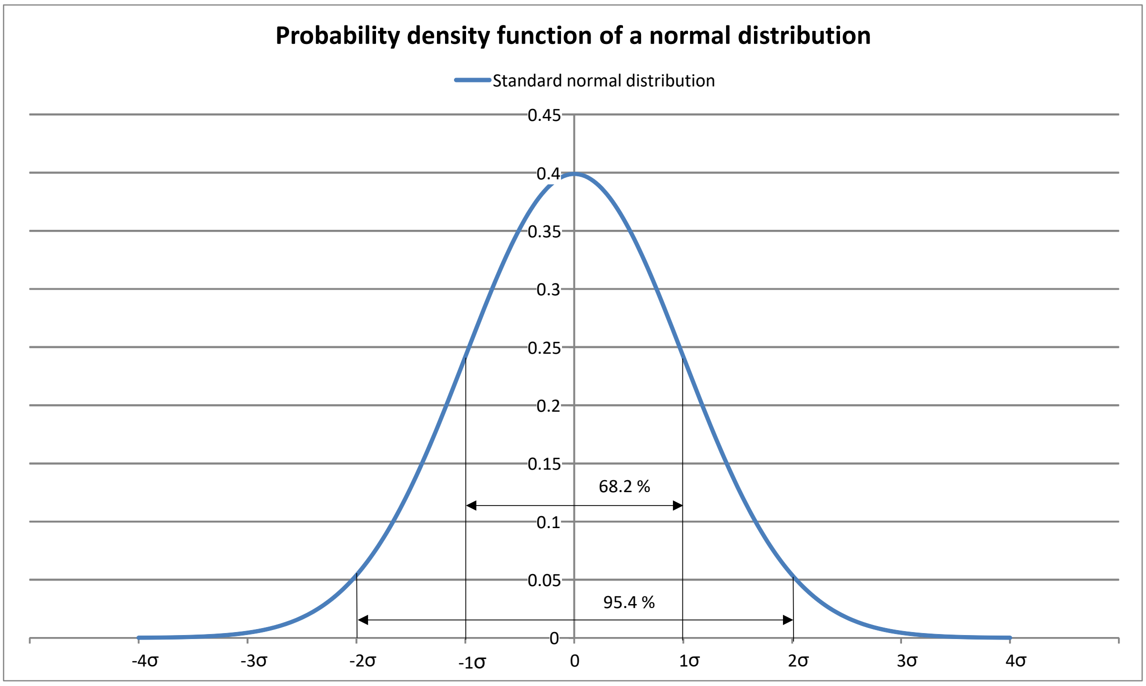

Figure A.1 Probability density function of a standard normal distribution.

Another useful distribution for physical parameters is the lognormal distribution; see Figure A.2 for an example of the shape of the probability density function. It is a continuous probability distribution where the logarithm is normal distributed. The main benefit of this relation is that the random variable cannot take negative values if it is lognormal distributed. For parameters where this is applicable, e.g. most parameters involved in an LCA such as emission factors and material amounts, the lognormal distribution is therefore a logical fit since it will guarantee that no false negative values are included in the analysis. The parameters μ and σ can be related to the normal distribution using Eq. A.9-A.10.

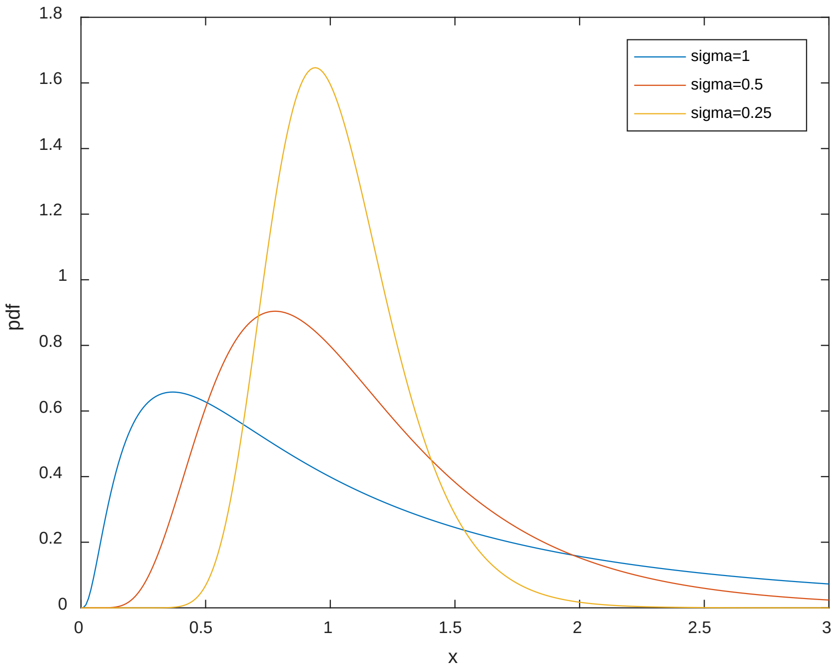

Figure A.2 Lognormal distribution with different standard deviations.

$\mu_{ln} = ln(\mu_N) - 0{,}5\sigma_{ln}^2$	Lognormal mean	(A.9)
$\sigma_{ln} = \sqrt{ln\left(\left(\frac{\mu_N}{\sigma_N}\right)^2 + 1\right)}$	Lognormal std. dev.	(A.10)

The third distribution commonly used is the triangular distribution. It is a continuous distribution with an upper and lower limit, see Figure A.3. In the figure, c is representing the expected value (mean) and the random variable can vary between a and b. this is a variant that can be useful for situations where it is not reasonable to think that a parameter can take an infinite value as for the normal and lognormal distributions.

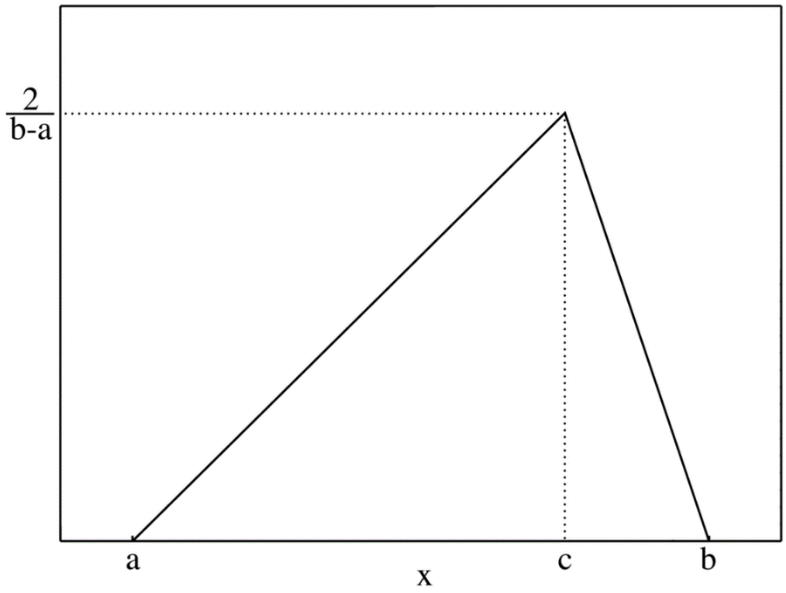

Figure A.3 Triangular distribution with lower limit a, upper limit b and expected value c.