LCA Methodology

Survey of Approaches to Improve Reliability in LCA

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Abstract. Limitations of data quality and difficulties to assess uncertainty are long since acknowledged problems in LCA. During recent years a range of tools for improvement of reliability in LCA have been presented, but despite this there is still a lack of consensus about how these issues should be handled. To give basic understanding of data quality and uncertainty in LCA, key concepts of data quality and uncertainty in the context of LCA are explained. A comprehensive survey of methods and approaches for data quality management, sensitivity analysis, and uncertainty analysis published in the LCA literature is presented. It should serve as a guide to further reading for LCA practitioners interested in improving data quality management and uncertainty assessment in LCA projects. The suitability of different tools for addressing different types of uncertainty and future needs in this field is discussed.

Keywords: Data quality, uncertainty; improving data quality; Life Cycle Assessment (LCA); sensitivity analysis; source of uncertainty; uncertainty assessment; uncertainty importance analysis; uncertainty, type of

Introduction

The reliability of life cycle assessment (LCA) is affected by dependence on data from different countries, different unit operations, different sources, data that is frequently not collected for LCA purposes [1], and more or less subjective methodological choices. LCA results are usually presented as point estimates, which strongly overestimate the reliability. This may lead to decisions that are unnecessarily costly, or mislead public perception about the environmental profile of a product or process [2]. These are long-since acknowledged problems. As noted already by Vigon and Jensen (1992, as cited in [2]), LCA practitioners lack systematic approaches for determining data quality, and need improved techniques for sensitivity and uncertainty analysis. Despite this, although this matter is often discussed, real assessments are rarely performed. In a review of 30 recent LCA studies, almost half of which acknowledged the uncertainty of the results, only three included some sort of quantitative or qualitative uncertainty analysis [3]. This is not surprising, since there is a lack of consensus about methodology. The recent ISO standard recommends the use of such methods [4–6], but gives little practical guidance. Early publications in this field focused on qualitative methods. Lately, a number of quantitative tools have been developed. Recently, frameworks addressing LCA reliability by integrating quantitative and qualitative approaches have been presented.

This paper is a survey of the literature regarding reliability in LCA. Key concepts of uncertainty in the context of LCA are explained. Quantitative and qualitative methods for data quality management, sensitivity analysis, and uncertainty analysis are presented. The intention of this paper is not to thoroughly explain all the details, but to provide an overview of the subject. It should also serve as a guide to further reading for those interested in improving the reliability of LCA studies.

Because of its close similarity to LCA, literature on material flow analysis (MFA) was also surveyed. Other related fields, such as risk assessment, were not surveyed. Focus is on uncertainty in the inventory phase of LCA, less on impact assessment. Weighting and interpretation is not within the scope of this paper.

1 Types and Sources of Uncertainty

Strictly, uncertainty arises due to lack of knowledge about the true value of a quantity. It should be distinguished from variability, which is attributable to the natural heterogeneity of values. Uncertainty can be reduced by more accurate and precise measurements. Variability cannot be reduced by further measurement, although better sampling can improve knowledge about variability. In this paper, 'uncertainty' encompasses uncertainty and variability. It also includes other factors that affect the reliability of LCA models, some of which are not even related to quantities. In the following, different types of uncertainty appearing in LCA models are presented.

Data inaccuracy: Data inaccuracy concerns the empirical accuracy of measurements that are used to derive the numerical parameter values [7]. Measurements can be subject to random error, which results from imperfections in the measuring instrument and observational techniques, or systematic error, which results from an inherent flaw or bias in the data collection or measurement process [2].

Data gaps: Missing parameter values may leave the model with data gaps [7].

Unrepresentative data: Data gaps may be avoided by using unrepresentative data [7], typically data from similar processes, but of unrepresentative age, geographical origin, or technical performance.

Model uncertainty: Model uncertainty is due to simplifications of aspects that cannot be modelled within the LCA structure, such as temporal and spatial characteristics lost by aggregation, linear instead of non-linear models, or derivation of characterisation factors [8].

Uncertainty due to choices: Choices are unavoidable in LCA. Because there is often not one single correct choice, there is uncertainty in choice, for instance, of allocation rules, functional unit, system boundaries, characterisation method, weighting method [8,9], marginal or average data [10], or technology level [11].

Spatial variability: Variability stems from inherent fluctuations in the real world. Although there are natural variations between different geographical sites, environmental interventions are usually summed up in the impact assessment, regardless of the spatial context. Examples of factors that vary over space are background concentration and human population density [8].

Temporal variability: Variations over time are relevant in both the inventory and impact assessment, as processes and factors in the receiving environment vary naturally over short and long time scales. Examples are process emissions, wind speed, and temperature. Another aspect is the chosen time horizon to integrate potential effects, which, for instance, applies to global warming potentials (GWP), photochemical ozone creation potentials (POCP) [8], and emissions from landfills [12].

Variability between sources and objects: Variability also appears between sources of the inventoried system (e.g. inherent variations in comparable technical processes), objects that determine the impact on the environment (e.g. human characteristics such as body weight or sensitivity to toxic substances), and preferences that determine the weighting of impacts [8].

Epistemological uncertainty: Epistemological uncertainty is caused by lack of knowledge on system behaviour [13]. It affects all phases of LCA. By nature, it is seldom acknowledged, and is very difficult to assess. A certain type of epistemological uncertainty arises when future systems are modelled, because the future is inherently uncertain.

Mistakes: Sheer mistakes are also a source of uncertainty [14]. As is the case with epistemological uncertainty, mistakes are seldom acknowledged and are very difficult to assess.

Estimation of uncertainty: Estimation of all types of uncertainty is in itself a source of uncertainty [15].

In **Table 1**, different types of uncertainty are linked to the point of introduction in the LCA process.

2 Improving Data Quality and Availability

Data quality relates to the degree of confidence in individual input data, in the data set as a whole, and ultimately decisions based on the LCA study [16]. It depends on the ability of data to satisfy stated requirements [4], its relevance for the particular application, and compatibility with the other input data [1]. Thus, it is a relative rather than an absolute measure. Data quality can be expressed through information about the data (meta-data) concerning uncertainty, re-

Table 1: Point of introduction in the LCA of different types of uncertainty, and examples of possible sources. Based on Huijbregts (1998a)

Type	LCA phase				
	Goal and scope	**Inventory**	**Choice of impact categories**	**Classification**	**Characterisation**
Data inaccuracy		Inaccurate emission measurements			Uncertainty in life times of substances and relative contribution to impacts
Data gaps		Lack of inventory data			Lack of impact data
Unrepresentative data		Lack of representative inventory data			
Model uncertainty		Static instead of dynamic modelling. Linear instead of non-linear modelling			Static instead of dynamic modelling. Linear instead of non-linear modelling
Uncertainty due to choices	Choice of functional unit, system boundaries	Choice of allocation methods, technology level, marginal/average data	Leaving out known impact categories		Choice of characterisation methods
Spatial variability		Regional differences in emission inventories			Regional differences in environmental sensitivity
Temporal variability		Differences in yearly emission inventories			Choice of time horizon. Changes in environmental characteristics over time
Variability between objects/sources		Differences in performance between equivalent processes			Differences in environmental and human characteristics
Epistemological uncertainty	Ignorance about relevant aspects of studied system	Ignorance about modelled processes	Impact categories are not known	Contribution to impact category is not known	Characterisation factors are not known
Mistakes	Any	Any	Any	Any	Any
Estimation of uncertainty		Estimation of uncertainty of inventory parameters			Estimation of uncertainty of characterisation parameters

liability, completeness, age, geographical area, process technology or technological level [17]. There are tools aiming to improve data availability and quality by ensuring 'good practice' in data collection and use. They cannot guarantee good data quality and low uncertainty, but may improve model transparency and credibility. The ISO standard addresses how data quality should be considered in LCA [4,5]. SETAC [16] presents an iterative framework for LCA data quality in energy, raw materials, environmental emissions, ecological health and human health data. Guidelines for systematically assessing and communicating data quality are provided by USEPA [2]. In the following, a number of qualitative and quantitative approaches to improve data quality in LCA are presented.

Standardisation: Standards are not imperative, but often become widely used because of the convenience. Following a standard may increase credibility by making it easier to communicate how a study was done. It is also more likely that good practice is used throughout the LCA, and that mistakes are avoided. Standards may be especially useful in reducing uncertainty due to choices in LCA [8], by outlining e.g. how to define functional units, draw system boundaries, and what allocation methods to use. The ISO standards will probably be widely accepted and used when entirely finalised.

Databases: Databases can make well-defined data more widely accessible. If the data base format includes data quality aspects, this facilitates uncertainty assessment. A major problem is to agree on a common format. Another is data collection; one must for instance overcome the data providers' fear of revealing proprietary information and misuse of data. The two most widespread initiatives to develop generic LCI database structures are the SPINE [18] and SPOLD [19] formats. Product, material, or process specific databases have been developed, without attempting to set standards for a common data-reporting format.

Data quality goals, DQG: DQGs specify in general terms the desirable characteristics of the data needed for the study [17]. They should be defined during the goal and scope phase of an LCA, and aid practitioners in structuring data acquisition. As data quality ultimately depends on the relevance and compatibility of data, DQGs will be tailored to the specific study [1,16]. The documented data quality may subsequently be related to the DQGs through the use of data quality indicators [17]. According to the ISO standard [4], data quality requirements should be included for the following aspects: 1) time-related coverage, 2) geographical coverage, 3) technology coverage, 4) precision, completeness and representativeness of the data, 5) consistency and reproducibility of the methods used throughout the LCA, 6) sources of the data and their representativeness, and 7) uncertainty of the information.

Data quality indicators, DQI: DQIs can be used to assess data quality, by either qualitatively or quantitatively relating the quality of LCI data to the DQGs. The ISO standard does not require use of DQIs, but asks for extensive reporting e.g. of data quality requirements, data collection, data sources, data quality assessment and treatment of missing data [5]. Examples of DQIs are: accuracy, bias, completeness, data distribution, precision, uncertainty, applicability, consistency, derived models, identification of anomalies, peer review, representativeness, reproducibility, stability, transparency, data collection methods and limitations, and references [2,16]. DQIs have also been defined slightly differently as semi-quantitative numbers attached to a data set, representing the quality of the data [17,20–22]. The quality of each data point or data set is assessed as qualitative DQIs in a so-called pedigree[1] matrix, and then translated to semi-quantitative numerical scores. It is important that the indicators are mutually independent, to avoid any kind of double counting.

Validation of data: Validation can be performed by establishing mass balances, energy balances, and comparative analyses of emission factors to reveal anomalies in data [5].

Parameter estimation techniques: Data gaps should be further treated to find a justified non-zero value, a justified zero value, or a calculated value based on reported values from similar technologies [5]. Imputation includes a wide range of procedures of replacing a missing value with a value considered to be a reasonable proxy or substitute [2]. Imputation methods suitable in LCA are e.g. mass balances to derive missing data on material flows, using data from similar technologies, or average industry data.

Additional measurements: Additional measurements and data research may provide useful information to improve data quality and availability [8].

Higher resolution models: Model simplifications are common and necessary in LCA. The use of non-linear models, dynamic models, and multi-media models can reduce model uncertainty and address temporal and spatial variability [8].

Critical review: Critical review, or peer review, shall be included to ensure scientific and technical validity, appropriate use of data, sound interpretation, transparent and consistent reporting, and consistency with the standard [4]. Peer review can address uncertainty due to choices, by judging choices on their merits [8]. However, it is often time consuming and costly, and may unfortunately remain inconclusive [1].

3 Sensitivity and Uncertainty Importance Analysis

Sensitivity is the influence that one parameter (the independent variable) has on the value of another (the dependent variable), both of which may be either continuous or discrete. Independent variables in LCA may be input parameter value (continuous), system boundary, allocation rule, model choice, or process choice (all discrete). Dependent variables may be output parameter values (continuous) or priorities between alternatives in a comparative study (discrete). Sensitivity analysis is a systematic procedure for estimating the effects on the outcome of a study of the chosen methods and data [5]. It can be applied with either arbitrarily selected ranges of variation, or variations that represent known ranges of uncertainty. The latter is also known as uncertainty importance analysis. Different types of sensitivity and uncertainty importance analysis are explained in further detail below.

[1] pedigree: the origin and the history of something

3.1 Sensitivity analysis

The ISO standard prescribes that sensitivity analysis should focus on the most significant issues, to determine the influence on variations in assumptions, methods, and data [6].

Tornado diagrams: Tornado diagrams illustrate the change in output parameter values for equal levels of change in input parameters. The model is run with low and high values for each parameter while all other parameters are held constant. The results are represented in lying bar graphs, the top bar representing the output range of the most sensitive parameter, and the bottom bar representing the least sensitive parameter [2], giving a graph shaped like an upside-down triangle, hence the simile to a tornado.

One-way sensitivity analysis: One-way sensitivity analysis determines the amount an individual input parameter value needs to change, all other parameters held constant, in order for output parameter values to change by a certain percentage [2].

Scenario analysis: Scenarios in LCA studies are descriptions of possible future situations, based on specific assumptions about the future, and are characterised by choice of system boundaries, allocation methods, technology, time, space, characterisation methods, and weighting methods [22]. Scenario analysis involves calculating different scenarios, to analyse the influence of discrete input parameters on either output parameter values or priorities.

Factorial design + multivariate analysis, MVA: Sensitivity analysis of output parameter values to changes in discrete input parameters can be performed by experimental factorial design and MVA [23]. Changes in the discrete input variables are represented by the high and low levels in factorial design. Scenario calculations replace the experiments. Each combination of high and low levels creates a unique combination of output parameter values. MVA is used to detect what independent variables have large influence on the dependent variables.

Ratio sensitivity analysis: In ratio sensitivity analysis, which is applicable only in comparative studies, a ratio is calculated to determine the percentage an input parameter value needs to change in order to reverse rankings between two alternatives. The sensitivity is expressed as the ratio of the difference between alternatives over individual process components. For instance, sensitivity of energy consumption would be expressed as the ratio of the difference in total energy consumption over the energy consumption in individual process steps [2].

Critical error factor, CEF: The CEF is a measure of the sensitivity of a priority between two alternatives to an input parameter value x. It is calculated as the ratio of the critical error Δx, i.e. variation in x required to bring about a change in priority, over the value of x, i.e. CEF = $\Delta x/x$ [24].

Table 2 lists the tools according to what type of input and output parameter they handle.

3.2 Uncertainty importance analysis

Uncertainty importance analysis focuses on how the uncertainty of different parameters contributes to the total uncertainty of the result [25]. A parameter can have large uncertainty, but still contribute insignificantly to the overall uncertainty. This is identified by determining the uncertainty of a parameter, either qualitatively or quantitatively, and combining this information with a sensitivity analysis. It gives more specific information than ordinary sensitivity analysis, and can be used to prioritise efforts to reduce uncertainty. It is equivalent to the selection of the main data [26], or finding key issues [27], and illustrated in **Fig. 1**.

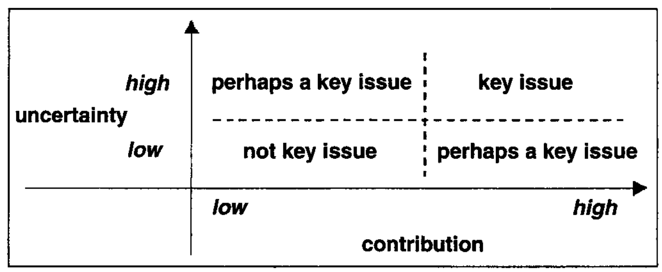

Fig. 1: Finding key issues in an uncertainty importance analysis, based on Heijungs (1996)

Quantitative uncertainty importance analysis: Quantitative uncertainty importance analysis can be performed in the same manner as a sensitivity analysis by Tornado diagrams, but using known uncertainty ranges of input variables rather than the same variation for each input variable. Variations in output will then reflect how the uncertainty of single parameters affects the results. Another means is to calculate

Table 2: Tools available to handle the different combinations of input and output variables in sensitivity analysis in LCA

Input variable	Output variable	
	1. Parameter value	**2. Priority**
1. Parameter value	Tornado diagrams One-way sensitivity analysis	Ratio sensitivity analysis Critical error factor
2. Allocation rule	Scenario analysis Factorial design + MVA	Scenario analysis
3. Boundary	Scenario analysis Factorial design + MVA	Scenario analysis
4. Model	Scenario analysis Factorial design + MVA	Scenario analysis
5. Process	Scenario analysis Factorial design + MVA	Scenario analysis

the correlation between model input and total model output. This requires total model uncertainty to be calculated prior to the uncertainty importance analysis. The tool Crystal Ball® has been used to calculate total uncertainty by Monte Carlo or Latin Hypercube simulation (c.f. 'Uncertainty analysis') [28,29]. This tool calculates uncertainty importance by computing the correlation between parameter uncertainty and model outcome. A third means is to calculate relative sensitivity [23], the ratio of the standard deviation σ_x of a parameter over the critical error Δx (variation in x required to bring about a change in priority), i.e. relative sensitivity = $\sigma_x/\Delta x$. This ratio is a measure of how large an influence x may have on the priority obtained.

Qualitative uncertainty importance analysis: Qualitative uncertainty importance analysis requires less numerical data, and is therefore less time consuming and closer at hand to use as a screening method. Main (important) data may be selected by first identifying key issues [26]. The contribution of individual processes is determined by dividing the elementary flows of a unit process by the cumulative elementary flow of the model. Processes with high contribution fit in the two right quadrants of Fig. 1. Qualitative assessment of uncertainty is done using DQIs according to [17], which are aggregated to a single DQI. High scores (high uncertainty) are placed in the upper quadrants.

4 Uncertainty Analysis

Uncertainty analysis is a systematic procedure to ascertain and quantify the uncertainty introduced into the results of a life cycle inventory analysis due to the cumulative effects of input uncertainty and data variability [5]. The ISO standard acknowledges that uncertainty analysis as applied to LCA is a technique in its infancy, but whenever feasible, such analysis should be performed to better explain and support the LCI conclusions. Uncertainty analysis can be performed by estimating the uncertainty of each parameter, expressing it as uncertainty distributions, and propagating the uncertainty through models to the final output. This is only possible when the uncertainty can be described by statistical functions. Other types of uncertainty, like data gaps and model uncertainty, require other techniques.

4.1 Estimating uncertainty in input data

Uncertainty in data is expressed quantitatively as a distribution over a certain range, which is ideally derived by statistical analysis of multiple measurements. LCA data, however, are more likely to be based on single point estimates. In this case some kind of expert judgement is needed.

Statistical analysis of actual data: If multiple measurements of a data point are available, the distribution can be determined by statistical analysis. Probability distributions can be derived by the observation of histograms in which the cumulative distribution of measurements is plotted [30]. For extensively measured parameters, classical statistical analysis can be used for curve fitting and to determine the mean and standard deviation [26]. Data based on little information may include a few measurements, which can be used to determine the endpoints of a uniform distribution, or if one value appears to be more likely, of a triangular distribution [26]. With few measurements, the t-distribution is more applicable than the common normal distribution, and gives a more conservative and defensible estimate of the level of uncertainty [22].

Expert judgement: Expert judgement can be used when statistical analysis is not possible. In its simplest form, expert judgement is simply a best estimate based on the experience of an expert in the relevant field. If for example one parameter relies on another for which the distribution is known, or if there is a similar process for which the distribution is known, these can be used as substitutes. A more formalised form of expert judgement is to derive distributions from the semi-quantitative DQI entries in a pedigree matrix (c.f. 'Data Quality Indicators'). Weidema and Wesnæs [17] presented the first developments of this method for LCI data. They distinguish between the basic uncertainty of data (inaccuracy), and the additional uncertainty (unrepresentativity) represented by the DQIs in the pedigree matrix, and present a method for combining the basic inaccuracy and additional unrepresentativity. A single DQI can also be assigned to each input data element on a sliding scale [21,31,32]. The DQIs are transformed to probability distributions by representing each DQI value by a default distribution. A similar method was developed for MFA studies. Data are categorised in five different uncertainty levels depending on the data source. Each level corresponds to a certain uncertainty interval [33].

4.2 Expressing uncertainty

Uncertainty distributions, defined by spread and pattern, describe how a parameter can be expected to deviate from its real value. Depending on the type of uncertainty and the amount of available information, different distributions can be used. Not all types of uncertainty can be expressed in the form of a mathematical distribution, e.g. uncertainty due to choices.

Probability distributions: Probability distributions are used to describe the uncertainty of inaccurate data, and express the probability that a variable will take on any number within a certain range (**Fig. 2**).

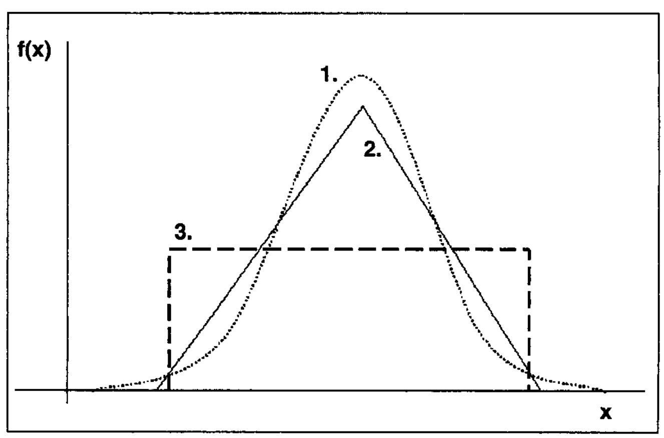

Fig. 2: Examples of probability distribution (1), uniform error interval (2), and vague error interval (3)

Frequency distributions: Variable data can be represented by frequency distributions, which organise raw data in classes and frequencies, most commonly presented as a histogram. Histograms can be approximated by the same type of distributions as used for probability distributions (Fig. 2).

Uniform (exact) error intervals: When the extreme values of a distribution are known, but not the distribution, or when data represent an interval, uniform intervals can be used [9,34]. In a uniform interval, all values are equally probable. This is a pessimistic representation, by over-estimating the tails and under-estimating the shoulders of the distribution (Fig. 2).

Vague error intervals: This is an extension of uniform intervals in which data is modelled as trapezes or triangles, and it gives a more optimistic representation of the distribution [9]. It can be used as a rough estimate of a probability distribution. It can also be used to model fuzzy data, the realism of which decreases with increasing accuracy [34]. In this context, vague intervals are known as fuzzy intervals or possibility distributions (Fig. 2).

4.3 Performing uncertainty analysis

Classical statistical analysis: Classical statistical analysis is widely used and accepted in other fields than LCA. It can be used if errors are given as probability distributions and with the assumption that the different data are independent [9]. Classical statistical analysis has been used in LCA, but with incomplete descriptions of important assumptions, determinations of probability distributions, etc. [13,22,35]. USEPA [2] presents uncertainty propagation formulas for random and systematic uncertainty, but without application to real data.

Bayesian statistical analysis: Bayesian statistical analysis is based on the assumption that subjective estimates of uncertainty can be treated with classical statistical analysis. In practice, most assertions about uncertainty in LCI data are based on subjective estimates. Thus, when classical statistical analysis is applied to LCI data, the assumptions underlying Bayesian statistics are implicitly made. In a method called 'Successive estimation', Bayesian statistical analysis is explicitly applied in combination with a kind of screening methodology, which systematically limits the inventory phase of an LCA [36].

Interval arithmetic: Uncertainty that is expressed as uniform intervals can be propagated by calculation with extreme values [9], or basic operations in interval arithmetic [34].

Vague error interval calculation: The propagation techniques for vague error intervals are derived from their uniform interval counterpart [9]. The propagation of fuzzy intervals in LCA matrices is described in [37]. Hedbrant and Sörme [33] suggest that large uncertainties are better expressed in terms of magnitudes leading to asymmetrical intervals. A methodology is presented and applied to MFA. A similar approach for LCA is presented by Huijbregts [28].

Probabilistic simulation: Two probabilistic, or stochastic, simulation techniques have been described in an LCA context, Monte Carlo and Latin Hypercube simulation. The steps of Monte Carlo simulation are 1) specify probability distributions for the model inputs, assumed to be independent, 2) sample randomly once from each input probability distribution, 3) plug the random samples into the model to obtain model outputs, and 4) repeat steps 2 and 3 N times to obtain N samples of each output [29]. The result is a frequency distribution of each output [15], which approximates the probability distribution and can be analysed with standard statistical techniques [29]. Larger sample size (N) gives better resemblance to the actual probability distribution. Assuming independence of input variables may overestimate output uncertainty. A means to avoid this is to include as a parameter, the parameter that two dependant variables have in common in the Monte Carlo simulation. Monte Carlo simulation with DQI-derived probability distributions is described in [21] and [31]. It has also been combined with a procedure for the selection of main data [26], and used to determine the significance of differences between alternatives [15,23]. Latin Hypercube simulation is similar to Monte Carlo, but segments the uncertainty distribution of a parameter in non-overlapping intervals of equal probability. A value is selected from each interval, according to the probability within the interval, leading to generally more precise random samples [8].

Scenario analysis: Scenario analysis, which is the same method as described in the sensitivity analysis section, involves calculating a few distinct scenarios. This method is useful when investigating uncertainty due to choices [8].

Rules of thumb: When any kind of detailed information on uncertainty is lacking, rules of thumb may be a useful strategy. These are generic estimates of the range of uncertainty for different categories of data. Finnveden and Lindfors [38] present rules of thumb for data categorised as: central non-substitutable resources, less central and substitutable resources, outflows calculated from inflows, other energy related emissions, other process specific emissions, total amount of solid waste, and specific types of solid waste. Based on data from Swedish sulphate pulp mills, Hanssen and Asbjørnsen [39] present rules of thumb for variation in data, making difference between comparisons within or between systems, and chain specific or branch generic data.

Expert judgement: Expert judgement can be used to estimate uncertainty distributions [8], but can also be used to estimate the total uncertainty of model output.

Table 3 provides an overview of the surveyed tools and approaches to address different types of uncertainty in LCA.

5 Frameworks

Because of the diversity of types and sources of uncertainty in LCA and of tools to handle it, uncertainty assessment requires guidance by a framework. Early frameworks were largely based on qualitative methods for data quality control, with suggestions of some quantitative tools for sensitivity and uncertainty analysis (e.g. [2,40]). They provide good information, but are no step-by-step procedures and would be difficult to apply in practice. The recent development of new tools has improved the possibility to develop a

Table 3: Overview of tools available to address (reduce and/or illustrate) different types of uncertainty in LCA. Based on Huijbregts (1998a)

	Data inaccuracy	Data gaps	Unrepresentative data	Model uncertainty	Uncertainty due to choices	Spatial variability	Temporal variability	Variability in objects/sources	Epistemological uncertainty	Mistakes	Estimation of uncertainty
Standardisation					x					x	
Data bases		x	x								x
Data quality goals	x		x								
Data quality indicators	x		x								
Validation of data										x	
Parameter estimation		x									
Additional measurements	x	x	x					x			
Higher resolution models				x		x	x				
Critical review		x	x		x				x	x	x
Sensitivity analysis	x		x	x	x	x	x	x			
Uncertainty importance analysis	x		x	x	x	x	x	x			
Classical statistical analysis	x					x	x	x			
Bayesian statistical analysis	x					x	x	x			
Interval arithmetic	x										
Vague error intervals	x										
Probabilistic simulation	x							x			
Scenario modelling			x	x	x	x	x	x			
Rules of thumb	x										

comprehensive framework. Work in this field is pursued, for instance, within the SETAC LCA Workgroup 'Data Availability and Data Quality'. Outcomes have been a framework for classification of uncertainty [8], and an overall framework for data uncertainty assessment [7]. The five-step procedure for uncertainty assessment in Maurice et al. [26] is in essence also a framework. New frameworks tend to converge towards the same main components; 1) scoping the uncertainty analysis, 2) selecting a method for modelling the uncertainties, 3) assessing the uncertainties in input data, 4) propagating the uncertainties through models, 5) reporting the uncertainty of output data [41].

6 Discussion and Conclusions

6.1 About the tools

Most of the tools in this inventory were not developed specifically for LCA applications. They are already well tried in other areas, and if necessary adjusted to the specific conditions of LCA. A few tools were actually developed for LCA, but even in these cases existing statistical methods form the basis. This is hardly surprising. Statistical analysis is generally well explored for other purposes, and the problems of LCA are encountered in other fields. The diversity of tools is considerable, which makes it difficult to settle for which to use. However, it is quite clear that because of the diverse types of uncertainty, not one method alone is enough. Thus, the range of methods appears quite necessary to cover all possible needs. Future efforts are needed to show what tools to use in different situations, and how they can be combined to be of the most use.

Standardisation of the LCA methodology can improve transparency and reduce methodological uncertainties. It is important that the standard is comprehensive and consistent. The ISO standard has been criticised for not considering all types of LCA applications and for being inconsistent in its recommendations of system boundaries and allocation procedures [42]. Development of standardised databases will improve data availability. A problem, but also strength of standards and databases, is that they require consensus among LCA practitioners. They are therefore time and resource demanding long-term solutions. DQGs and DQIs are simpler approaches. These methods can be tailored to the specific needs in each case, which makes them flexible. Although mainly qualitative, they can be of good help in improving data quality. Making additional measurements of inventory data or using higher resolution models to achieve more accurate estimates of modelled phenomena are seemingly simple approaches, but often too time and resource demanding.

Sensitivity and uncertainty importance analyses give better knowledge and understanding of a model and its behaviour. This may be more valuable for overall credibility than elaborate uncertainty assessment or spending resources to improve data quality. Uncertainty importance analysis is also a good screening methodology, which can help to prioritise in a model improvement process. Drawbacks of sensitivity analysis are that intensive effort is required to perform sensitivity analysis of all parameters, combinations with potential synergism are overlooked, and it makes no direct consideration of relative probability [29].

Classical statistical analysis was the first quantitative tool to be proposed for quantitative uncertainty analysis in LCA. But apparently it has not been very successful. Despite many theoretical descriptions, it has only been used in limited assessments. The reason appears to be the difficulty of statistically deriving uncertainty distributions. A natural solution is to use Bayesian statistical analysis, which is similar to classical statistical analysis, but with uncertainty distributions based on expert judgement. Probabilistic simulation is often mentioned as an especially promising technique. It allows for the use of any type of uncertainty distribution, depending on what information is available [8,26,27], and different distributions can be mixed in the same simulation. It can also be used with all kinds of operations [26]. An LCA model already implemented as a computer model requires little additional modelling, which makes it suitable for large models for which it is complicated to propagate uncertainty analytically.

The difficulty of estimating uncertainty of input data is a severe limitation to all types of uncertainty analysis. Expert-based methods need to be used. Using semi-quantitative DQIs to derive uncertainty distributions is more formalised than most expert-based approaches, which makes it attractive. However, the same pedigree score, for instance of technological representativity, may be of different relevance for different processes [26]. SETAC [16] means that not enough empirical work has been done to quantitatively characterise the expected increase in imprecision induced by differing degrees of data pedigree, and that score-based uncertainty distributions are still purely hypothetical.

Strikingly few publications were found on uncertainty in MFA. Despite its similarity to LCA, there appears to be considerable difference in interest in uncertainty. One explanation may be that LCA has a longer history and is more widespread, thus more researchers have had more time to explore these issues. Another explanation may be that LCA is used in commercial applications and for actual decision making more often than MFA, which is still mainly a research tool. This may put very different demands on reliability.

6.2 About uncertainty analysis in LCA

The credibility of LCA can be questioned if the results cannot be accompanied by adequate uncertainty analyses. Presenting results merely as point estimates without uncertainty distributions is an unreasonable overestimation of their exactness. However, there is also a risk that incomplete methods for uncertainty analysis give a false sense of credibility. One must carefully consider how to present and use the results. The aim must be to help decision makers form an opinion of how much confidence to have in the results, but there is a risk that the increased complexity of the results do nothing but add to confusion.

It is likely that quantitative uncertainty analyses of many comparative LCAs would not be able to show any significant differences between the alternatives, either because estimates of uncertainty are too conservative, or because LCA practitioners actually have too much trust in the reliability of the results. Still, there is a general perception that LCA is useful and de facto can be used to infer environmental impacts of products and processes. In any case, the usefulness of LCA does not only lie in the quantitative estimates of emissions and environmental impact. Just as important, although less tangible, is what is learned about the system while carrying out an LCA project. For this purpose the very process of assigning DQIs and performing sensitivity and uncertainty analyses is more important than the actual quantitative outcome of these analyses.

A practical objection to applying any of these approaches is that any effort to improve data quality and assess uncertainty will inevitably require more data collection than what would otherwise be needed. As LCA is already rather time and resource demanding, LCA practitioners quite naturally feel reluctant to adding more complexity to the analyses. This requires careful prioritisation of what issues to focus on.

6.3 What is needed?

It is obvious that some kind of tools to address data quality and uncertainty are needed. But it is also obvious that it must not be too complex. In most cases it would not be practically feasible to spend the necessary time and resources to collect the necessary data, and thus the tools would not be applied. It is not satisfactory to develop tools that generate impressive accounts of data quality and uncertainty if LCA practitioners do not feel they are worthwhile to use. A good tool must lead to an actual improvement of data inventory routines, model insight and results presentation, as well as be of help to decision makers. Simple tools may be dismissed as not being accurate enough, but they may well win in the long run, simply by being practically usable.

To limit the amount of extra work, it is important to focus the efforts to the most important areas, and areas where large improvements can be gained at limited efforts. Uncertainty importance analysis can be used as a screening method to identify the key issues to focus on. Less demanding is to prioritise efforts based on experience of what types of uncertainty are usually most important. Methodological choices (system boundaries, allocation methods, technology level, and marginal/average data) tend to have large influence, which may well override many other types of uncertainty. This type of uncertainty cannot be eliminated, but is rather easily illustrated by identifying the relevant alternatives and performing sensitivity analysis by scenario modelling.

The best way to help practitioners and ensure a comparable standard of LCA studies would be to agree on a framework for data quality management and uncertainty analysis. Taking the above considerations into account though, it seems difficult, if not stupid, to develop a framework that outlines in detail what should be done and how. Of greater use would be a framework that points out the important aspects of data quality and uncertainty in LCA to the practitioner, guides through the considerations one must make regarding for instance desired results, time and resources, describes what one can do to address different issues, and describes how to do it. This survey should be useful in developing such a framework.

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