

TREATMENT OF UNCERTAINTIES IN LIFE CYCLE ASSESSMENT

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ABSTRACT: Spurred by European Union directives along with increased interest among US initiatives, life cycle assessment (LCA) is becoming a common tool used in the measurement and evaluation of environmental performance and overall sustainability. Life cycle assessment is an analytical technique for assessing potential environmental, social, and economic burdens and impacts of a given product or process, encompassing all stages of life cycle, from raw material production through end-of-life management. LCA provides metrics that can be used to measure progress toward sustainability. A life cycle assessment includes a number of phases: goal and scope definition, inventory analysis, impact assessment and interpretation. Each of these phases has significant associated uncertainties. Decisions made without regard to these uncertainties may be flawed. This paper describes common sources of uncertainty, methods for quantifying uncertainty, and methods for propagating input and model uncertainties in order to determine the resulting uncertainties in final estimated environmental impacts. An example application is presented to illustrate that even if only the most critical uncertainty sources are identified, it is feasible to obtain useful information about uncertainties in a given assessment. This application also illustrates the need to prioritize the many sources of uncertainty present in a given LCA. There are many practical challenges to consider in this very broad field, but also a variety of areas in which further achievements can be made. This paper serves to illustrate opportunities to further apply the tools of probabilistic modeling to the important and rapidly growing field of life cycle assessment.

1 INTRODUCTION

Spurred by European Union directives such as WEEE (Waste Electrical and Electronic Equipment), ROHS (Reduction of Hazardous Substances in Electrical and Electronic Equipment), and ELV (End of Life Vehicles), along with increased interest among US initiatives such as LEED (Leadership in Energy and Environmental Design), life cycle assessment (LCA) is becoming a common tool used in the measurement and evaluation of environmental performance and overall sustainability. Life cycle assessment is an analytical technique for assessing potential environmental, social, and economic burdens and impacts, encompassing all stages of life cycle, from raw material production through end-of-life management. LCA provides metrics that can be used to measure progress toward sustainability (Keoleian and Spitzley 2006).

As outlined by ISO 14040 series standards, any life cycle assessment requires a number of phases beginning with goal and scope definition, inventory analysis, impact assessment, and interpretation. Each of these phases, along with their associated da-

tabases and models, has significant associated uncertainties. Decisions made regarding design development and improvement, strategic planning, public policy making, or product marketing without recognizing this uncertainty may potentially be flawed.

A general motivation for quantifying uncertainties is to increase the transparency of LCA data and results. Uncertainty is undeniably present in many aspects of analysis, and treating it explicitly will aid in several ways. This paper provides an overview of sources of uncertainty, methods for quantifying uncertainty, and methods for propagating input and model uncertainties in order to determine their effect on uncertainties in the final estimated environmental impacts. An example application is used to demonstrate how uncertainties in impacts can be used to support improved decision-making by users of LCA tools. Impacts include adding the ability to identify alternate systems whose environmental impacts appear to differ at first glance, but for which the impacts are actually statistically insignificant due to uncertainties in the inputs. A second impact is the ability to identify important uncertainties and so focus uncertainty-reduction efforts in the most critical areas.

After describing the importance of this topic and identifying tools for performing relevant analysis, prospects for future progress in this field are considered. There are significant practical challenges to implementing explicit uncertainty treatment, but also many areas in which further achievements can be made. The few examples where uncertainty has been treated explicitly in LCA assessments illustrate the opportunities that exist to further apply probabilistic modeling to this important and rapidly growing field.

2 THE VALUE OF QUANTIFYING LCA UNCERTAINTIES

A general motivation for quantifying uncertainties is to increase the transparency of LCA data and results. Uncertainty is undeniably present in many aspects of analysis, and treating it explicitly will aid in several ways, as outlined below.

2.1 *Decision support*

When making comparisons among design alternatives, apparent differences in impacts may be misleading if the uncertainty in impacts is large enough to overwhelm any relative differences between alternatives. Quantification of these uncertainties will support informed decision making (Basson and Petrie 2004; Cowell et al. 2002; Lenzen 2006; 2000).

When design alternatives are being evaluated in the presence of significant uncertainties, large uncertainties may make it impossible to determine whether one design alternative is truly superior to another. This type of situation arises frequently in other fields, and the statistics topic of hypothesis testing is a mature field used, for example, to evaluate the true benefit of a new drug that is being considered for approval by a regulatory agency. In the field of LCA, Basson and Petrie (2004) have considered similar problems and termed their approaches “distinguishability analysis.” Whatever the specific name and technique, it is important to recognize that apparent differences in impacts from design alternatives may be small enough relative to uncertainties in estimated impacts as to be insignificant. Consideration of uncertainty is thus critical in this case for sound decision making.

2.2 *Transparency*

If model inputs are uncertain and the uncertainty is hidden or ignored by the analyst, then this lowers the credibility of the LCA. An opponent could propose alternative, valid, model inputs that lead to differing results. Without openly acknowledging the uncer-

tainty that leads to both sets of model inputs being plausible, there is no clear resolution to these situations, reducing the value of the LCA results (Weidema 2000).

2.3 *Quality competition*

Reduced uncertainty (e.g., in databases) is desirable, and by transparently displaying uncertainties there will be increased motivation to improve data quality (Ciroth 2003). This is true both for general data sources as well as for individual case studies.

2.4 *Planning of information gathering exercises*

If resources are available to refine elements of an LCA analysis, it is helpful to understand what uncertainties exist in a model (uncertainty quantification), and what uncertainties have the greatest impact on results and potential decisions (sensitivity analysis). Formal uncertainty treatment procedures, such as “pre-posterior analysis” in decision theory, can help to efficiently use resources to improve a model by collecting more data to reduce uncertainties (Benjamin and Cornell 1970).

More concretely, a SETAC-Europe LCA working group on data availability and data quality has developed a framework for modeling data uncertainty and the Danish Environmental Protection Agency has proposed a data collection strategy for reducing uncertainty in life cycle impacts (LCI) (National Renewable Energy Laboratory 2007).

3 TYPES OF UNCERTAINTY

Uncertainty can refer to lack of knowledge (epistemic uncertainty) or inherent randomness (aleatory uncertainty) in any model input. A variety of specific uncertainty sources are listed below, with an emphasis on their relevance to specific issues in LCA. The varying types of uncertainty need not be treated differently, but their classification can serve as a useful accounting exercise to ensure that all relevant uncertainties are quantified. Other lists of uncertainty sources are provided elsewhere (Björklund 2002; Lenzen 2006).

3.1 *Database uncertainty (e.g., missing or unrepresentative data)*

Available data in an LCA database may not exactly represent the quantity being studied. This can result, for example, from differences in the product/impact being studied or from regional or temporal differences in inventories/impacts (Danius 2002; Huijbregts 2001; RTI International ; Schuurmans 2003; Sugiyama et al. 2005). This type of uncertainty will

be considered in the example application below. With industrial production increasingly taking place in less developed countries, the uncertainty of both data collection and trustworthy reporting diminishes the validity of life cycle assessments based on these datasets.

3.2 *Model uncertainty*

The models relating design decisions to impacts may have uncertainties that could affect the quality of the assessment outputs. Simplified models may not capture exact cause-and-effect mechanisms, or data regression may have the wrong functional form. There may be unknown interactions among model parameters. This category can also more generally include lack of knowledge about the functioning of the system being studied (Asbjomsen 1995). The combined use of Economic Input/Output Life Cycle Assessment (EIO-LCA) techniques with process-based LCA has been proposed to mitigate this uncertainty (Williams 2007). However, such approaches do not address aleatory uncertainty associated with stochastic variables such as discount (interest) rates for future economic, social, or environmental costs or impacts.

3.3 *Statistical/measurement error*

Estimating distributions of properties from a limited set of sample data creates statistical variability. The sample data may also have measurement errors, or the standards used to collect and quantify the data may not be known.

3.4 *Uncertainty in preferences*

An analyst's choices regarding modeling of preferences and value judgments can play a large role in carrying out a life cycle assessment. Decisions regarding LCA goal and scope definitions (i.e. functional unit and input cut-off rules), allocation of co-product impacts and recycling streams, determination of industry performance (average industry performance, best-in-class, worst-in-class), and life cycle impact assessment (LCIA) and characterization techniques can be treated as uncertainties. Quantifying analyst preference and judgment using uncertainty techniques lends greater confidence in life cycle assessments regardless of the skill and experience of the analyst.

3.5 *Uncertainty in a future physical system, relative to the designed system*

LCA is performed on a conceptual model that may not exactly represent the physical system that will be constructed. Differences may arise from lack of knowledge about what materials will be used in the

system (e.g., more than one material supplier may meet the design specifications), future design changes, and human error. Uncertainty is also derived from inaccurate model of product use phase in terms of future service or maintenance schedules and end-of-life estimates.

4 QUANTIFYING UNCERTAINTIES

Quantifying uncertainties is an important step in accounting for their effects when making decisions. It is easiest to quantify basic variables, and much more difficult to quantify outputs from complex or opaque models. Using this line of thinking, Notten and Petrie (2003) make an argument that model inputs, and their associated uncertainties, should be specified at the most basic possible level. This is consistent with the longstanding approach in structural reliability of modeling "basic" random variables rather than "derived" random variables, to facilitate data collection and focus the uncertainty modeling on the true sources of uncertainty rather than derived functions of these uncertainty sources (Melchers 1999). In some cases, using basic variables rather than derived variables also makes it easier for sources of uncertainty to be specified as independent.

Another area in which uncertainties must be quantified is database values. Understanding the quality of data from a database is of great importance, for quantifying uncertainty as well as planning to reduce uncertainties. Data quality rankings may be either qualitative or quantitative. While quantitative measures are clearly preferable in a formal uncertainty assessment, in some cases only qualitative measures are available. Due to the complex environmental mechanisms between energy, materials, and emissions quantified in a life cycle inventory and any category endpoints (i.e. global sea level rise, deforestation), uncertainty in impacts will likely be more subjective than uncertainty in inventory. In the past, LCA consulting firms such as Franklin Associates have published a Data Quality Index that ranged from A to E depending on the overall quality of the data point. LCA practitioners should be confident in the use of "A" and "B" data points. As the number of "D" and "E" points increases, modelers should be more wary of the results. This has been replaced somewhat by the establishment of statistical distributions for many datasets. An overview of existing implemented data is provided by Heijungs and Frischknecht (2005).

If raw measurement data is available (e.g., from databases or case studies), then uncertainties might be calibrated using this data. Classical tools from probability and statistics, such as parameter estimation and hypothesis testing, will be useful for this

type of problem (Benjamin and Cornell 1970). In cases where data is not available, expert judgment may be required to quantify uncertainties. Experts may be able to use their experience to quantify the various uncertainties described above. A typical challenge using this approach is that the LCA experts may not be experienced with probabilistic modeling, and probabilistic modelers may not have the LCA experience necessary to accurately quantify uncertainties. The field of expert elicitation provides guidance on overcoming these challenges and obtaining quantifications that aren't unduly biased the experts personal preferences or preconceived ideas (Arkes et al. 1997).

5 PROPAGATING UNCERTAINTIES

Typically, a fundamental question in an uncertainty analysis is "to what extent do uncertainties in input values produce uncertainties in model outputs?" To do this, uncertainties must be "propagated," using one of several methods. There are a number of examples in the literature where LCAs have been performed with special care made to treat uncertainties. Most of these examples come from outside of the building industry (see, for example, Andr e et al. 2004; Basset-Mens et al. 2004; Contadini 2002; Dones et al. 2005; Ferret et al. 2004; Geisler ; Rosenbaum et al. 2004; Zhang and Vidakovic 2005).

Lloyd and Ries took a survey of 30 LCAs to identify what uncertainty propagation methods are being used (Lloyd and Ries 2007). They found that 14 mentioned uncertainty explicitly, two performed qualitative uncertainty analysis, and only one performed quantitative uncertainty analysis. Clearly these tools are not yet widespread, due primarily to challenges associated with characterizing uncertainties.

5.1 Monte Carlo simulation

This appears to be the most popular approach in LCA. Some LCA software platforms, such as SimaPro and Umberto, now provide the ability to calculate uncertainty using Monte Carlo analysis. The Ecoinvent LCA database includes quantitative uncertainty values for parameters in many of its processes.

5.2 Approximate analytical methods

Analytical results are available under specific circumstances such as linear relationships between input and output variables (which can be approximated for any problem using Taylor Series expansions in the First-Order Second-Moment

method). This approach is less computationally expensive than Monte Carlo analysis, which can be an advantage if any part of the model required complex numerical modeling (Baker and Cornell 2003). It uses slightly more complex mathematics than Monte Carlo, however, which appears to have limited its adoption in LCA.

5.3 Sensitivity analysis

This calculation consists of systematically varying input parameters, to determine how sensitive the outputs are to each input. This is not a complete uncertainty propagation procedure, but it is useful for understanding a system and it helps the analyst omit treatment of input parameters that are quickly seen to be unimportant to the final results.

6 APPLICATION

6.1 Integrating uncertainty analysis into LCA through source prioritization

Integrating uncertainty into life cycle assessment begins with identification and prioritization of uncertainty sources. Due to the high level of uncertainty in many aspects of life cycle assessment, originating from both epistemic and aleatory sources, the prioritization of the sources can be leveraged to help focus specific characterization efforts. With limited resources to investigate entire supply chains and complex production systems, the characterization of "low hanging fruit" which make up the bulk of overall assessment uncertainty becomes increasingly important.

The identification and prioritization of uncertainty in life cycle assessment begins with the construction of a life cycle assessment model. For consistency across models and approaches, adherence to ISO 14040 series standards is followed. This initial assessment is done for three reasons:

1. Characterization of uncertainty can then be focused on the largest life cycle impact phases.
2. Primary sources of uncertainty can be classified as primarily epistemic or aleatory in nature.
3. Results are used to gauge effects of uncertainty on wider system impacts.

Life cycle assessment focuses on the reduction of total impacts into groups of impacts allocated to each phase of the life cycle. The majority of impacts associated with highly durable, active systems such as buildings, automobiles, and airplanes are as-

sociated the use phase. In such systems, the energy and emissions associated with raw material extraction, material production, and manufacturing and construction are small compared to overall life cycle impacts. In the case of buildings, over 90% of life cycle energy consumption and emissions are associated with the use phase (Keoleian and Spitzley 2006). By focusing uncertainty characterization on the greatest life cycle phases, significant resources dedicated to uncertainty analysis can be saved.

Within each life cycle phase, different types of uncertainty can dominate. In the raw material extraction, material production, and manufacturing phases, the processes and systems in question are well known. Therefore, uncertainty in these phases arises from inaccurate datasets, limited sample sizes, and process modeling errors. In the use and end-of-life phases, uncertainty may be more random primarily derived from inherent randomness in service life performance in a given load environment or functional obsolescence due to swings in consumer preference. The classification of specific uncertainty sources as epistemic or aleatory in nature not only allows for improved treatment of uncertainty but also a broad check to ensure that all relevant uncertainties are identified.

6.2 Demonstrating the need for uncertainty characterization and prioritization

To illustrate the effects that uncertainty can have on life cycle assessment results, a case study built upon the life cycle assessment of a standard residential home built in the US is adopted. Keoleian et al. (2001) quantified the life cycle impacts of a 2450 ft² (228 m²), two-story home built in the Midwestern US with an internal usable volume of 26,960 ft³ (763 m³) over a life span of 50 years. In addition to the structure itself, domestic services were provided by a set of common appliances and entertainment products including refrigerator/freezer, range, range hood, microwave, toaster, dishwasher, sump pump, cloths washer, cloths dryer, computer, TV, radio, and heated aquarium.

The total primary energy consumption and total global warming potential (GWP) were inventoried over the material and construction phase, use phase, and demolition phase of the structure. These are shown in Table 1. Of total global warming potential in the use phase, 49.4% can be contributed to electricity generation with the remainder being contributed to natural gas production (precombustion emissions) and combustion. This results in a use phase global warming potential burden resulting from electricity consumption of approximately 406,000 kg CO₂-eq or approximately 45% of total life cycle

greenhouse gas emissions based on average US electricity production.

Table 1. Residential home primary energy consumption and global warming potential by life cycle phase (Keoleian et al. 2001).

Life Cycle Phase	Primary Energy Consumption (GJ)	Global Warming Potential (kg CO ₂ eq)
Materials and Construction	942	79560
Use	14482	931486
Demolition	31	2235
Total	15455	1013281

Using average US electricity production, Keoleian et al. failed to characterize the geographic uncertainty associated with this production. As shown in Table 2, greenhouse gas emissions resulting from electricity production can vary considerably depending on the geographic location of production within the US. Taken from Kim and Dale (2005), distinct differences in CO₂ production alone (not considering other greenhouse gases) exist between the various North American Electric Reliability Council regions throughout the US. Greenhouse gases CO₂ and NO_x are shown in Table 2. SO_x emission values are included for further illustration.

These emission differences are the result of varying fuel mixes used throughout the United States for electricity generation. The US grid is broken into a number of distinct generation regions to increase system reliability. In each geographic region, the generation portfolio is comprised of a different set of bituminous coal, sub-bituminous coal, lignite, petroleum, and natural gas fired plants along with nuclear and renewable sources. Each generation technology and fuel has an associated life cycle greenhouse gas impact.

Table 2. Selected environmental profiles in regional electricity systems based on consumption (Kim and Dale 2005).

NAERC Region	CO ₂ (g per MJe)	NO _x (g per MJe)	SO _x (g per MJe)
ECAR	240.68	0.63	1.46
ERCOT	190.96	0.4	0.33
FRCC	167.44	0.43	0.6
MAAC	150.8	0.35	1
MAIN	187.22	0.46	0.76
MAPP	227.35	0.54	0.62
NPCC	119.23	0.21	0.49
SERC	184.33	0.52	0.68
SPP	259.6	0.67	0.67
WSSC	135.59	0.39	0.27

Incorporating the generation and emission differences between various NAERC regions into the use phase global warming potential profile shifts the re-

sulting life cycle greenhouse gas emission profile significantly (Table 3) for the residential house being investigated. As shown, depending on the building site location (i.e. which NAERC region), the portion of GWP that can be attributed to use phase electricity production ranges from 35% in the extreme northeastern US (NPCC) to 54% in Midwestern US plains (SPP).

Table 3. Impacts of incorporating regional generation and emission differences in use phase and total life cycle global warming potential (GWP) emissions.

NAERC Region	Use Phase GWP from Electricity Production (kg CO ₂ eq)	Total Life Cycle GWP (kg CO ₂ eq)	Percentage of Total Life Cycle GWP from Use Phase Electricity (%)
US Average (Keoleian et al.)	460154	1013281	45.4
ECAR	604787	1157914	52.2
ERCOT	511022	1064149	48.0
FRCC	398503	951630	41.9
MAAC	339900	893027	38.1
MAIN	421945	975072	43.3
MAPP	609476	1162603	52.4
NPCC	300050	853176	35.2
SERC	440698	993825	44.3
SPP	642294	1195420	53.7
WSCC	332867	885994	37.6

Considering such a wide range of differences, uncertainty analysis can play a significant role in informing sustainability-oriented design choices to ensure the robustness of decision processes and associated guidelines. To illustrate, due to the high portion of electricity use phase global warming potential seen in the Midwestern US plains (Kansas, Oklahoma, and parts of western Texas), design choices should focus on the constructing residential buildings and purchasing appliances which minimize use phase electricity consumption. In the northeastern US more emphasis should be placed on lowering GHG emissions in the material production and construction phases, or improving the insulation of the structure to reduce non-electricity energy consumption for heating during the use phase.

This application serves as one simple example of how variation in modeling data, and the inherent random nature in which use phase impacts are accrued, can lead to significant differences in life cycle assessment results. In dealing with this uncertainty, significant improvements can be made to the field of life cycle assessment and the decisions built upon such assessments.

7 CHALLENGES

7.1 Quantifying inputs

There are many mature tools available for describing the distribution of possible values for an uncertain quantity, but actually quantifying the level of uncer-

tainty for the many inputs requires a major effort. One must synthesize across many sources of uncertainty and use many types of information. Comprehensive uncertainty assessments will likely require subjective judgments for some aspects.

7.2 Standardization

Are treatments of uncertainties between design alternatives consistent? Are quantified uncertainties representing what the user thinks they are? Are LCA users speaking about uncertainties with a common language? For systematic treatment of model uncertainty, the uncertainty in a simplified model relative to a complex model might be quantified and standardized for use in industry analyses.

The completion of process-based life cycle assessments is governed by the ISO 14040 series of standards. While the existence of uncertainty is acknowledged within these standards with regard to life cycle inventories, no attempts are made to standardize the quantification or mitigation of uncertainty. Therefore, a final step for completion of an ISO-compliant LCA is a critical review by an independent internal expert, an independent external expert, and an interested party panel. Through rigorous review by a series of experts and stakeholder groups, the validity of the life cycle assessment framework and results are confirmed.

While no effort toward standardization is made by ISO, as part of the third-party review an “analysis of the indicator results, for example sensitivity and uncertainty analysis or the use of environmental data, including any implication for the results” must be conducted. The public disclosure of such analysis results is also required for any comparative assertions based on life cycle assessment results (ISO 1997).

8 CONCLUSIONS

A review and explanation of uncertainty quantification in life cycle assessment has been performed. Uncertainty is undeniably present in many aspects of analysis, and treating it explicitly will aid in several ways. A general motivation for quantifying uncertainties is to increase the transparency of LCA data and results, and to prevent erroneous decision-making that might result from neglecting uncertainties. An overview was provided of sources of uncertainty, methods for quantifying uncertainty, and methods for propagating input and model uncertainties in order to determine their effect on uncertainties in the final estimated environmental impacts. A variety of motivations for quantifying uncertainty have been proposed and summarized, and an exam-

ple application has been presented to demonstrate that even if only the most critical uncertainty sources are identified, it is feasible to obtain useful information about uncertainties in a given assessment. This illustrated the need to prioritize the many sources of uncertainty present in a given LCA.

Before initiating further research efforts on this topic, one should first ask whether it is even possible to develop general guidance and recommendations for uncertainty treatment while recognizing that individual projects have varying needs and goals. LCA is a very flexible tool that was designed for use by a wide variety of industry sectors, processes, and users, the development of general guidelines; thus, development of general recommendations for the treatment of uncertainty in LCA is a major challenge. It may not be feasible to address all aspects of uncertainty modeling in all situations, but more work on specific topics may have a big impact on improving the value of LCA's. For example, it would be valuable to further characterize the uncertainty associated with processes common to many LCAs (i.e. impacts of production and use of electricity, natural gas, and some basic materials). From case studies, we can assess typical impacts of common uncertainties, and make recommendations regarding the impact of those uncertainties on a larger body of LCAs. There are a variety of practical challenges to consider, but also many opportunities to further apply the tools of probabilistic modeling to this important and rapidly growing field.

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