LCA Case Studies

Application of Data Quality Assessment Methods to an LCA of Electricity Generation

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Abstract

Background, Goal and Scope. For the life cycle assessment (LCA) tool to provide maximum benefit for decision makers, the uncertainty of its results should be reported. Several methods for assessing uncertainty have been developed, but despite recent efforts, there remains disagreement about their merits.

Objectives. The objectives of the study were to review several assessment methods for estimating numerical and qualitative uncertainty of impact scores and recommend an appropriate uncertainty assessment scheme. The methods review has been conducted on the basis of an LCA case study regarding the comparison of the use of either brown or black coals in Australian electricity generation.

Results and Discussion. Each assessment method indicated greater uncertainty in the impact scores calculated for black coal use than for brown coal use. Due to overlap of the uncertainty ranges in calculated impact scores neither of the coals could be regarded environmentally preferred.

Conclusions. Both qualitative and quantitative methods were found to provide useful information about the uncertainty of calculated impact scores for the case study. Methods that combine qualitative and quantitative uncertainty provided no additional benefits, and obscured much of the information gained from using qualitative methods.

Recommendation and Outlook. It is recommended that LCA results should include separate numerical (using Monte-Carlo simulation) and qualitative uncertainty assessments. When the ranges of calculated impact scores for compared options overlap, the normalised difference method is recommended.

Keywords: Australian electricity generation; coal; data quality; data uncertainty; life cycle assessment (LCA)

Introduction

One of the stated purposes of the life cycle assessment (LCA) tool is to provide decision makers with information about the environmental effects of choices. Despite the ISO standards' recommendation that data quality parameters be reported [1], data quality assessment is not current practice in LCA studies [2,3,4]. Therefore, in practice, decision makers must make a judgement about the accuracy of the LCA. However, without some systematic assessment of data quality there is no adequate basis for that judgement.

One method of expressing the practitioner's confidence in the results, and increasing the probability of trust, is to acknowledge the range of possible (or likely) outcomes. The environmental impact scores calculated using average, maximum, and minimum data values might result in entirely different relativities for alternatives. Thus, the range of impact assessment scores obtainable from the LCA should be reported, and possible conclusions discussed.

The aim of this paper is to review and compare several methods to determine, which method, or combination of methods, provides the best option to assess the uncertainty of the LCA results. This is achieved by undertaking an assessment of data quality with regard to a case study on environmental impacts in electricity generation from Australian black and brown coals, which is part of a wider study on electricity generation in Australia [5].

1 Review of Uncertainty Methods

1.1 Introduction

Traditional methods for determining the range of a result (known as error analysis), used in other types of assessment, have proven inadequate for LCA, as they cannot include so many different types of uncertainty [6,7]. Thus, significant effort has occurred to develop a generalised method that can be applied in LCA.

Guidance on data quality analysis for LCAs can be obtained from three main sources. Firstly, the International Organization for Standardization (ISO) 14040s series of standards state that data quality requirements should be documented during the development of the study's Goal and Scope Definition [1], including: age, geography, and technology information; the precision, completeness, and representativeness of the data; the consistency and reproducibility of the LCA model; the data sources and their representativeness; and the uncertainty of the information [1]. If there is a need for an accurate and detailed study [8] three types of analyses are recommended: gravity analysis (e.g. Pareto), which determines data with greatest contribution; uncertainty analysis, which determines range of possible results based on in-

Table 1: Data quality pedigree matrix by Weidema and Wesnæs [9]

Indicators	Indicator Score				
	1	2	3	4	5
	Independent of the study in which the data are applied:				
Reliability of the source	Verified data based on measurements	Verified data partly based on assumptions or non-verified data based on measurements	Non-verified data partly based on assumptions	Qualified estimate (e.g. by an industrial expert)	Non-qualified estimate or unknown origin
Completeness	Representative data from a sufficient sample of sites over an adequate period to even out normal fluctuations	Representative data from a smaller number of sites but for adequate periods	Representative data from an adequate number of sites but for shorter periods	Representative data from a smaller number of sites and shorter periods, or incomplete data from an adequate number of sites and periods	Representativeness unknown or incomplete data from a smaller number of sites and/or from shorter periods
	Dependent on the goal and scope of the study:				
Temporal correlation	Less than 3 years of difference to year of study	Less than 6 years of difference to year of study	Less than 10 years of difference to year of study	Less than 15 years of difference to year of study	Age unknown or more than 15 years of difference to year of study
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 production conditions	Data from an unknown area or with very different production conditions
Technological correlation	Data from enterprises, processes and materials under study	Data from processes and materials under study but from different enterprises	Data from processes and materials under study but from different technology	Data on related processes and materials but from same technology	Unknown technology or data on related processes or materials but from different technology

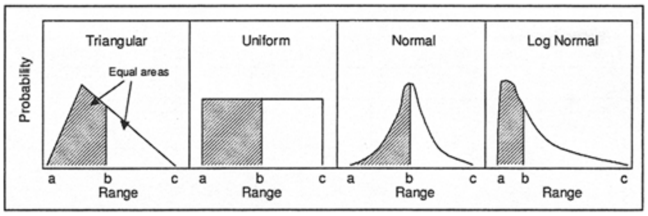
dividual data uncertainties; and sensitivity analysis, which determines the effect that changes in data and methods have on the results [1,8]. In this paper, only the uncertainty analysis is considered, as this is an area of great complexity in LCA. Secondly, the Centre of Environmental Science (CML) Guide [7] recommends that the ISO requirements be followed, with the optional use of a 'Pedigree Matrix' and/or one of the proposed uncertainty frameworks (e.g. [6], or [3]). Finally, the Society of Environmental Toxicology and Chemistry (SETAC) European working group on 'Data Availability and Data Quality' [4] provide both a framework for uncertainty, and possible methods to calculate data uncertainty. The framework classifies data uncertainty into 'data inaccuracy' and 'lack of specific data' (i.e. data gaps and unrepresentative data). Data gaps are to be filled using either input-output modelling, data from similar products, or mass balances. Unrepresentative data uncertainty is estimated by applying uncertainty factors, obtained through further analysis of material inputs and outputs, to account for temporal, geographical and technological differences, using the pedigree matrix of Weidema (**Table 1**). Total uncertainty is obtained using the Monte Carlo simulation method (see Section 1.2). Empirical justification of the uncertainty factors and data ranges used is also necessary to ensure the relevance of the conclusions. This is a substantial task for even a simple LCA study.

A review of methods indicated that three types existed: a quantitative assessment considering only numerical uncertainties in input data (see Section 1.2); a qualitative assessment using indicators to consider a range of input data aspects (see Section 1.3); and a quantitative assessment, where the qualitative input data aspects are converted into quantitative uncertainty (see Section 1.4).

1.2 Numerical uncertainty

Quantitative assessment methods use input data variability information to obtain a cumulative uncertainty value for an output, using uncertainty propagation. Proposed analytical methods for uncertainty propagation include uncertainty propagation, interval methods, fuzzy logic simulations, and Bayesian statistics [3]. However, stochastic models, such as Monte Carlo [3,10] or its modified form Latin Hypercube [3] simulation, are most commonly used, as they are able to include any number of different probability distributions for the individual data points [3]. These stochastic methods randomly vary all individual data values, using their individual uncertainty distributions. For example, if a data point has a mean at 100, with a distribution such that the probability that it is 100 is 50%, while the probability that it is 95 is 12%, then for 100 iterations, a result for the entire system will be calculated using a value of 100 for this data point in approximately 50 iterations, and a value of 95 in approximately 12 iterations. As the calculation involves many such data points, all varying independently from each other, the result calculated for each iteration will also vary. The collected results from all these iterations form a new profile, which represents the uncertainty of the result.

Where possible, actual ranges and probability distributions of data collected are used; however, when data is limited, 'rules of thumb' [11,12] may be used to produce likely ranges. In this case, the mean value, and estimated minimum and maximum values, or a 95% confidence interval, can be used to define a probability profile for each data source. Many probability profiles may be chosen, however the most common are: triangular, uniform, normal, and log-normal (**Fig. 1**).



Fig, 1: Common probability distributions (a = minimum, b = average, c = maximum)

Despite the seeming completeness of such methods, they do suffer a number of limitations. Firstly, they consider only one aspect of data quality, variability from the true mean, ignoring aspects such as the data's fitness for purpose, and most importantly, how accurately the system modelled in the LCA matches reality [6,13]. Secondly, combining the uncertainties of the different types of data used at different points in the LCA model has proven difficult [6,14], e.g. data uncertainty and uncertainty due to allocation between products. Thirdly, the uncertainty of the LCA model itself is unknown [7], and cannot be tested against real systems, as the outputs have no defined spatial or temporal characteristics [6]. Lastly, the final uncertainty value can only be calculated with confidence for a specific impact category [6]. While relative contributions of specific impacts to total environmental impact can be postulated, for example by reference to expert opinion, such relativities are necessarily subjective and their uncertainty cannot be quantified on a scientific basis.

1.3 Qualitative uncertainty

To measure the qualitative uncertainty in an LCA model each of the attributes of the system that add to it are judged independently and given a score; a lower score in most cases represents higher quality. The scores may then be interpreted on three levels [6]:

- Data level (individual data sources)
  Example indicators: see Table 1
- Process level (physical or notional subsections of the system)
  Example indicators:
  - Completeness (all flows considered in process) and
  - Applicability of assumptions for allocation and aggregation
- System level
  Example indicators:
  - Completeness (all processes considered)
  - Applicability of assumptions for aggregation and impact category choices

This method is often called the 'Pedigree Matrix' method [15].

Many groups of indicators have been proposed to describe an LCA system. For example, Weidema and Wesnæs [9] proposed the indicators shown in Table 1. Each of these indicators is data level only, while others (i.e. [13], or [16]) list indicators at many levels. Some declare that these indicators may not be aggregated because the scores do not represent an amount of quality (i.e. [9], [17], or [19]), and thus the aggregated scores could not be used for comparisons. However, other researchers (i.e. [16] and Lindeijer et al.[1]) suggest otherwise, as the combined scores are only designed to indicate, rather than measure.

In one method, proposed by Wrisberg [16], quality indicators are aggregated to obtain the total system quality, using equal weights for all environmental flows. Consider for example, the case where an environmental impact result is developed from two material flows, with data quality scores of (3, 2, 4, 1, 1) and (1, 1, 2, 3, 4), for the five indicators respectively, and contribute 33% and 67% of the environmental impact result respectively. The final indicator scores will equal the sum of the indicators divided by two, or (2, 1.5, 3, 2, 2.5).

In another method, proposed by Rousseaux et al. [13], the quality performance of each data point is compared to some decided target quality goal score (e.g. 2 out of 5). To determine the performance of a particular process or system, the percentage of data points that pass this criterion are compared (called 'Acceptability'). For example, if a hypothetical process A has three data points with quality indicator scores of (1, 2, 1, 3, 4) for point B, (2, 3, 2, 4, 1) for point C, and (3, 3, 3, 3, 3) for point D, and the chosen quality goal score is 2, then for the first indicator: point B's (1) and C's (2) score passes, but point D's score (3) fails. Thus the 'acceptability' of process A's first indicator is 66%[2]. If the practitioner is attempting to reduce qualitative uncertainty (i.e. indicator scores) then another parameter, the ratio of the quality score variance to the average quality score is calculated. Variance here is the sum of each points difference from the mean divided by the number of points. Using the above example, the average of process A's first indicator is 2, its variance is 2/3, and thus its variability ratio is 33%[3]. If this ratio is high, then the quality scores have a wide spread, and may thus include some very 'good' (1) and 'bad' (5) scores. In this case, the total quality may be improved by reducing the number of 'bad' scores. When the ratio is low, then the quality scores are in a narrow range and greater numbers of data points must be changed to improve the total data quality score.

1.4 Methods for combining numerical and qualitative uncertainty

Numerical and qualitative uncertainty results, obtained from the methods shown in Sections 1.2 and 1.3, together may be used to indicate uncertainty in impact results. Alternatively, an individual data point's qualitative uncertainty can be converted into a quantitative uncertainty profile (called 'additional uncertainty') and added to the data point's numerical uncertainty profile (see Section 1.2). This combined profile can then be used to generate a quantitative uncertainty profile for the impact results, adding process and system level qualitative uncertainties at the appropriate calculation points during a stochastic calculation method (see Section 1.2).

Three different methods have been proposed for the conversion of qualitative uncertainty into additional uncertainty:

[1] From: Lindeijer, E., Berg, N.W. van den and Huppes G. (1997), *Procedure for Data Quality Assessment*, Report for Rioned (in Dutch), September (discussed in [6]).

[2] For the remainder of the indicators the 'acceptability's' are 33%, 66%, 0%, and 33%.

[3] For the remainder of the indicators the 'reliability's' are 8%, 33%, 7%, and 58%.

Table 2: Calculation table to obtain the data quality indicator of Kennedy et al. [10]

% of Attainable Data Quality (x)	Aggregated Data Quality Indicator (I)	Shape Parameters		Extents (% variation from mean)	
		α	β	A	B
100	5	5	5	–10	+10
87.5 ≤ x < 100	4.5	4	4	–15	+15
75 ≤ x < 87.5	4	3	3	–20	+20
62.5 ≤ x < 75	3.5	2	2	–25	+25
50 ≤ x < 62.5	3	1	1	–30	+30
37.5 ≤ x < 50	2.5	1	1	–35	+35
25 ≤ x < 37.5	2	1	1	–40	+40
12.5 ≤ x < 25	1.5	1	1	–45	+45
0 ≤ x < 12.5	1	1	1	–50	+50

Beta probability functions [10]; additional estimated uncertainty ranges (twice the coefficient of variation[4]) for each type of data elements [18]; and obtaining estimates of variation due to the problem indicated[5] [9]. The first method (of Kennedy et al. [10]) integrates a chosen list of indicators through a parameter, x, known as the percent of attainable data quality (Equation 1). It does not recommend a prescribed set of qualitative indicators, but recommends that they be developed from previous experience of using the method. To illustrate the Kennedy et al. method, if a data point has a value of 100, with quality scores of (2,2,3,2,1) for five indicators, then the sum of quality scores is 10, the sum of maximum quality scores is 25 (maximum score for each indicator is 5), and the sum of minimum quality scores is 5 (minimum score for each indicator is 1). Thus in this example x equals (10-5)/(25-5) times 100 = 25%. The data quality indicator (I) is obtained from **Table 2** (example I is 2). This indicator (I) is then used to create one or more Beta probability distributions, which are modified normal distributions, described using two shape parameters (α and β) and its extents (A and B). These parameters are estimated from I using expert knowledge, or from Table 2 (in the example: α = 1; β = 1; A = –0.4 times the value of the data point or –40; and B = 0.4 times the value of the data point or 40).

$$x = \left(\frac{\sum \text{Quality Scores} - \sum \text{Minimum Quality Scores}}{\sum \text{Maximum Quality Scores} - \sum \text{Minimum Quality Scores}} \right) x 100\,\% \quad (1)$$

The second method (Meier [18]) is designed for data, process, and system level indicators, including indicators for assumptions, valuation, and impact category considerations. Its conversion factors are developed from previous experience in using the method. For example, the conversions in **Table 3** were developed for the geographical correlation indicator. In this case, additional data uncertainty is calculated for the chosen indicators using the additional uncertainties shown in Table 3, and is characterised by a normal distribution with standard deviation of 1/4 of this range. For the example data above, (2,2,3,2,1), the additional uncertainty will equal the sum of that for each indicator: ±(10+10+20+10+5)%, or ± 55%. Using the mean value of our example, 100, then the variation is ± 55, and the standard deviation is (45 – (–55))/4 or 27.5.

Table 3: Example additional uncertainty calculation table for the geographical correlation indicator of the Meier method [6]

Quality Score (I)	Additional Uncertainty Range (±%)
1	5
2	10
3	20
4	30
5	50

Despite the mathematical nature of these methods, the results are still subjective, reliant on expert judgement to determine the variation caused by each indicator score [17]. As a single range for each impact category is provided, the perceived credibility of LCA study results may be enhanced [3]. However, as knowledge of the bases of the conversion methods are limited among practitioners and decision makers alike [3], the combined confidence parameter may unintentionally reduce understanding of the uncertainty in the results.

1.5 Methods for comparing system quality scores

Quality assessment results are generally presented using box plots (**Fig. 2**) [19]. The cut-off probability for the boxes is chosen by the decision-maker [19], based on the allowable risk, i.e. 95% (95 out of every 100 possible cases is included). These plots may prove helpful, when there is minimal overlap, as in cases A and B. However, when there is significant overlap, as in cases B and C, it is more difficult to determine which is the better option.

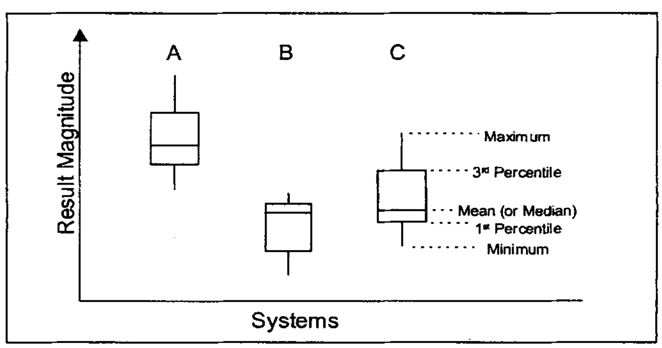


Fig. 2: Box plots of notional system quality scores (the positions of the 1st and 3rd percentiles is dictated by the desired confidence)

[4] The coefficient of variation is equal to the standard deviation divided by the mean value.

[5] For example, to update energy consumption data taken from an older process, the increased efficiency of the new process could be used. In the general case, this requires additional research into each data point, and thus considerable additional resources may be necessary.

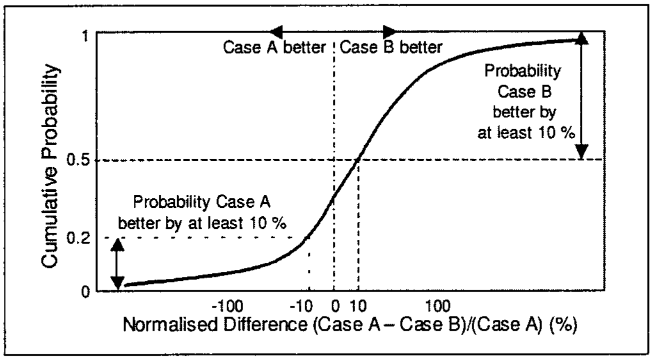


Fig. 3: Example cumulative normalised difference plot

The usual method of resolving this difficulty is to perform the LCA on the difference between the cases (i.e. Case A minus Case B). If the generated quality box plot is entirely above zero, then Case A is definitely greater than Case B. When the value straddles zero, a value judgement must be made to decide between the options. Generally, the positions of the mean (or perhaps the median) values are used as evidence of difference, and the degree of crossover reported, qualitatively or quantitatively.

Another proposed method involves the generation of a normalised difference probability distribution [19], characterised as the ratio ($Result_{(Case\ A)} - Result_{(Case\ B)})/Result_{(Case\ A)}$. If this ratio is positive (i.e. 0.12) then Case A is said to be better than Case B by the magnitude of the ratio (i.e. 12%). Conversely, if the ratio is negative, then Case B is said to be better than Case A, again by the magnitude of the ratio. It is also proposed [19] that by preparing a graph of the cumulative distribution function of this ratio (**Fig. 3**), using a Monte-Carlo simulation, the probability of one case being significantly better than the other (say by a 10% margin) can be determined. For example, in Fig. 3 there is a 50% probability that Case B is better than Case A by at least 10%, while there is only a 20% chance that Case A is better than Case B by the same margin. This step is considered essential only if the alternatives cannot be separated through closer inspection of the system.

1.6 Current practice

Data quality assessment is not current practice in LCA studies [2,3,4]. A recent survey of LCA studies reported that only 4 out of 30 studies explicitly reported problems of uncertainty, and of these only one produced a quantitative analysis and two produced a qualitative analysis [2]. This situation however can be considered an improvement from an earlier study of data quality and databases [20], which reported no use of uncertainty analysis. During preparation of this case study on electricity generation, a similar trend was observed. Out of approximately 30 reports, only one report used a quantitative quality assessment technique (confidential report), one used a simplified quantitative method on a process level [21], another gave a qualitative discussion of uncertainty issues [22], and a few others gave indicative ranges based on the variability of a single data value, in this case electricity generation efficiency (i.e. [23,24]).

This practice may reflect the already considerable time requirements for many LCAs and a belief that detailed quality assessment does not provide sufficient benefit to decision makers to justify its expense. It has also been suggested that the current unsatisfactory state of data quality analysis and its lack of transparency [7] provides little incentive to include it in LCA studies. Thus, research into possible simplifications is important to reduce the need for detailed analysis of each datum [3], and the time required for data quality analysis [14]. Integration of data quality methods into existing LCA software programs could reduce time requirements [4].

2 Electricity Generation Case Study

2.1 Introduction

Electricity is one of the most important contributors to a nation's economy. In Australia, almost all electricity is produced using fossil fuels (~90%), and of these black coal (55%) and brown coal (or lignite) (30%) are the dominant contributors [25]. The environmental impact of electricity from these two fuels is highly significant; for example, in 1998 black and brown coal electricity generation contributed 20% and 15% respectively of Australia's total greenhouse gas emissions [26].

2.2 Inventory data and impact assessment

Inventory data was obtained from both confidential and public sources, and refers to the black coal electricity generation industry in New South Wales and Queensland (Australia), and the brown coal electricity generation industry in Victoria (Australia). Ranges for some data were estimated using the 'rules of thumb' of Finnveden and Lindfors [11].

The impact assessment involved the use of impact factors provided by CML [7]. The impact categories chosen for the data quality study were climate change, acidification, and resource depletion, because they are generally regarded as the most significant effects of power generation (e.g. [21–24]). The molecular species of most significance for climate change are CO_2, CH_4 and N_2O from the combustion of fossil fuel, while for acidification they are NO_x and SO_x also from fuel combustion, and for resource depletion they are coal and other fuels. The impact factors used in the analysis also contain uncertainties, which will contribute to the uncertainty of the calculated impact scores. Important information such as temporal and spatial spread, dose-response, and thresholds, required for site specific studies, are ignored, which makes the conversion of material data to environmental effects a highly uncertain process [2]. This uncertainty was not considered in this analysis.

2.3 System descriptions

Both systems consist of mining, processing, and transport of coal, and electricity generation and transmission (**Fig. 4**). However, due to the quite different nature of the coals (**Fig. 5**) there are significant differences between black and brown

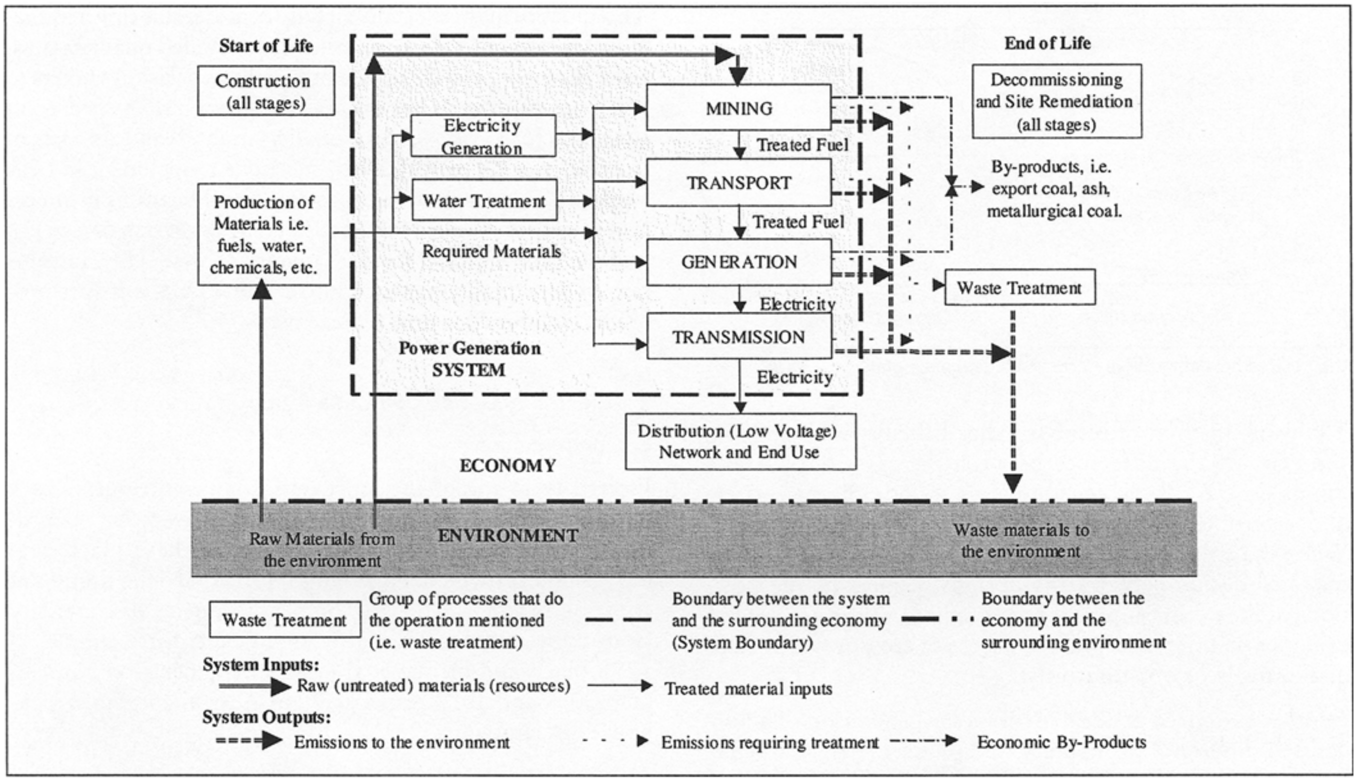


Fig. 4: System boundaries for the LCA case study: electricity generation from black or brown coals

coal generation. In the black coal system some 25% of the coal is obtained from underground mines, and the remainder (75%) is obtained from surface mines. When used for domestic power production, the coal is only crushed and milled before consumption. Coal transport is by three methods: conveyors (62% of coal, short range (5 km)); trucks (17%, mid range (10 km)); and trains (21%, long range (210 km)). Coal may be stored at any stage of this system. In the brown coal system, coal is continuously mined from surface mines, and the high moisture content ensures the coal is soft, removing the hazards associated with the use of explosives, and the drilling operations necessary for black coal mining. Coal processing involves only simple fan milling, without grinding or crushing. Coal transport is exclusively via conveyors over short range (5 km). Coal storage is considered uneconomic.

The technology used in producing electricity has a major influence over the system output, as it defines the magnitude of coal flow through the initial stages. Both the black and brown coal systems used pulverised fuel-steam turbine technology. The greater moisture content of brown coal reduces its electrical generation efficiency (electrical energy over coal energy consumed) below that of an equivalent black coal plant (i.e. 23–34% brown coals, 30 to 40% black coals). As a result, the environmental performance of a brown coal system is generally assumed worse than the equivalent black coal system.

For both systems, the transmission occurs over high voltage wires to a substation, where the electricity's voltage is reduced for use in a distribution grid. Losses for both transmission grids are between 1 and 3%. The functional unit is one unit (MWh) of electricity delivered to this substation. Final distribution and end use of electricity are excluded from the systems because of the highly complex, and location specific nature of such systems.

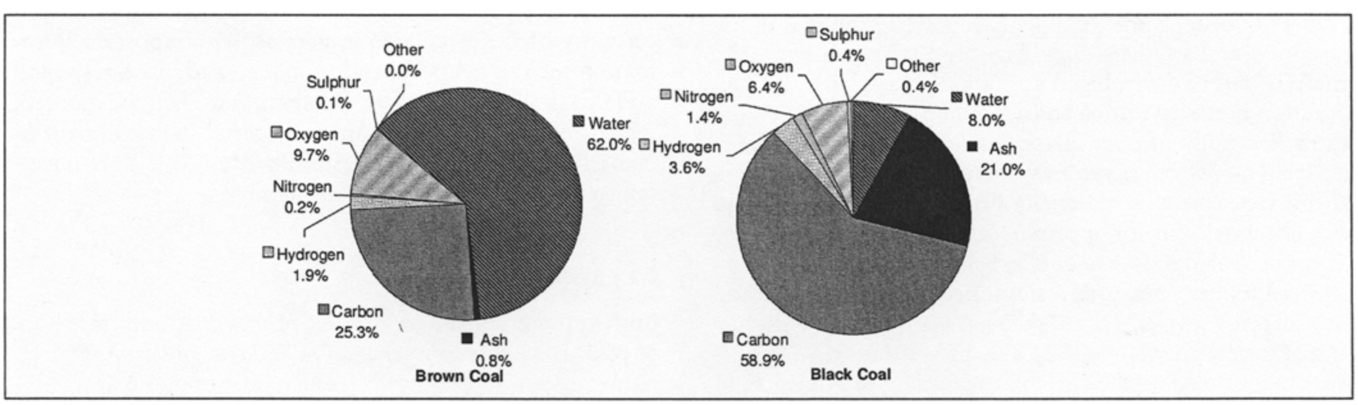


Fig. 5: Australian black and brown coal constituents

3 Results and Discussion

3.1 Numerical uncertainty

Monte-Carlo simulations (explained in Section 1.2) were completed for both black and brown coal cases. Varied in the simulations were all data necessary to produce the climate change, acidification, and resource depletion indicators, except the impact factors (see Section 2.2). Each simulation involved 10000 calculations of each of these indicators, using XlSim© software. As many data point's uncertainty distributions were unknown, a number of common types were tested: triangular, uniform, normal and log normal (see Fig. 1). The maximum, minimum and mean values were used to define these distributions. The effect of this choice was found to be considerable (**Table 4**). The minimum mean value and standard deviation were obtained when using normal distributions, and the maximum standard deviations were attained when using uniform distributions. In the calculation of the acidification potential of the brown coal system the use of triangular and uniform distributions was found to increase the mean impact value by over 300%. This was caused by the highly skewed uncertainty distribution of the NO_x and SO_x emission factors, whose mean and minimum values were similar and distant from their maximum values. Their actual distribution was approximately log-normal (see Fig. 1), and neither the uniform or the triangular distributions could successfully approximate a log-normal distribution. For a uniform distribution, its outputs will be spread evenly in the range, and so its mean must lie halfway between its extents. For a triangular distribution, its output distribution is limited such that its average must lie between 29 and 71% of the distance between its extents. The fact that such problems can occur, limits the practicality of standard, arbitrary distributions.

When the distribution for each data point cannot be determined (i.e. if insufficient data can be collected within the available time frame), then it is recommended that a skewed distribution, such as the triangular or log-normal distributions, be used. They allow the average data point to be closer to either its minimum or maximum, and can be defined from a data point's average, minimum, and maximum values (see Fig. 1). In addition, the triangular distribution probably overestimates the true uncertainty profile, which is likely to approximate a skewed normal distribution, and thus provides a conservative estimate.

Some additional simulations were completed to determine which data were the greatest contributors to the final uncertainty profile (**Table 5**). During these simulations, the uncertainty profile for a chosen data point was removed, and thus the chosen data point was then constant in all simulations. When the power station efficiency was held constant the standard deviations and therefore the variability of the results were substantially reduced and the uncertainty ranges of the black and brown coal systems became similar. The greater uncertainty in the black coal data was due to the

Table 4: Results of a numerical simulation using the Monte-Carlo technique (SD = standard deviation)

System	Probability Distribution Type	Climate Change ($kg_{CO_2\text{-eq.}}$ per MWh)		Acidification ($kg_{SO_2\text{-eq.}}$ per MWh)		Resource Depletion ($kg_{Sb\text{-eq.}}$ per MWh)	
		Mean	SD	Mean	SD	Mean	SD
Black Coal							
	Average	1040	–	6.77	–	6.37	–
	Triangular	1082	309	7.98	2.90	6.51	1.92
	Uniform	1080	460	9.32	4.53	4.55	2.89
	Normal	1038	255	6.88	2.21	6.40	1.53
	Log Normal	1099	334	7.38	2.83	6.79	2.16
Brown Coal							
	Average	1341	–	3.47	–	10.9	–
	Triangular	1319	102	12.0	6.1	11.1	0.6
	Uniform	1386	138	19.3	8.2	11.3	0.9
	Normal	1338	76	3.34	4.67	10.9	0.5
	Log Normal	1346	76	4.92	3.38	10.9	0.5

Table 5: Simulations indicating the influence of individual data uncertainty on indicator uncertainty (Triangular distribution, SD = standard deviation), A from Table 4

Constant	Climate Change ($kg_{CO_2\text{-eq.}}$ per MWh)			
	Black Coal		Brown Coal	
	Mean	SD	Mean	SD
Triangular, No Variable Fix[A]	1082	309	1319	102
Power Station Efficiency	1084	65	1368	59
Coal Lost in Transit	1111	277	1382	101
Coal CO_2 Emission Factor	1055	304	1363	80
Coal-Bed Methane	1085	298	1319	102

wide range of electricity generation efficiencies encountered within the study scope, Australia. This variation is due to differences in age and design of electricity generation plant. Also an individual power station's efficiency may also fluctuate during operation, due to variances in fuel quality, ash deposition on boiler tubes, operation during startup and shutdown, and by capacity utilisation effects. In the brown coal case, the variation due to uncertainty in the emission factor of CO_2 from coal combustion was also a significant contributor, as the moisture content, and thus the amount of carbon per kg of raw coal, varies significantly between the three coal sources. Other data uncertainties, such as the amount of coal lost as dust in mining and transportation, and coal-bed methane emission factor, were found to be minor contributors to the uncertainty of the results.

3.2 Qualitative uncertainty

Qualitative uncertainty measures for the black and brown coal systems were obtained using a single set of indicators (see Table 1) to ensure a fair comparison. It may be significant that these indicators are all data level indicators, while both methods were developed to include process and system level indicators in their intended indicator sets.

Qualitative uncertainties calculated using the method of Wrisberg (see Section 1.3) are shown in **Table 6**. They have been aggregated for each system section independently as well as for the total system to highlight the areas in which quality is poorest (i.e. has highest score). It was observed that reliability and completeness were the major contributors to qualitative error for both black and brown coal cases. This was due to the use of some data that was unverified or based on assumptions (i.e. poor reliability), and the lack of data for some facilities within the desired region (Australia). The '%' column was added to show the relative contributions of each section to the total indicator. Thus, as the transmission data indicators contribute less than 10% to the totals, increases in the quality of the transmission data will not substantially decrease the totals. Mining and transport contributed a higher than expected proportion to the totals, because in this method each important data flow is given equal weighting. Thus, even though the generation stage dominated the impact results (for climate change and acidification), it had a similar number of streams contributing to the scores as the mining and transport stages, and so did not dominate the Wrisberg totals. Therefore, the final score was indicative of the quality of the inventory collection procedure (i.e. how good relative to theoretical perfection). However, this method fails to establish whether quality is good in data that counts towards the impacts. As such, this method's results cannot be used in discussions of the quality of the environmental impact results.

Total qualitative uncertainties calculated using the method of Rousseaux et al. (see Section 1.3) are shown in **Table 7**. When a target quality score of 1 or 2 was set, the acceptability (i.e. the percentage of inventory scores equal to the target score or less) for each indicator was lower for black coal than brown coal. This indicates that the data quality of the brown coal system was better than for the black coal system. For the reliability indicator, the use of industry data for much of the brown coal system, as opposed to the majority use of published reports for black coal system data, led to better scores. Also significant was the smaller number of existing brown coal systems (3 c.f. black coal >10), allowing more complete representation of the average brown coal system, and thus a better completeness score. Comparing variability scores, it was noticeable that both systems had high temporal scores, indicating a wide spread of indicator values. In the inventory of both systems most sources were recent (within three years of the year of study), which means an indicator score of 1 or 2 (see Table 1). However, a number of very detailed older sources (10 years prior to the year of study) were also used, giving indicator scores of 5. This was also true for the brown coal system reliability score, where a small number of estimates had to be made (indicator score 5), while most data was verified and based on plant measurements (indicator score 1). This method thus shows more promise in locating and identifying the cause of deficiencies in data quality. However, like the method of Wrisberg, this method does not weight data quality based on the data's

Table 6: Qualitative uncertainty scores calculated using the Wrisberg method

Section	Score									
	Reliability		Completeness		Temporal		Geographical		Technological	
	Score	%	Score	%	Score	%	Score	%	Score	%
Black Coal										
Mining	2.87	35	3.60	40	1.20	29	1.60	39	1.67	42
Transport	3.57	20	4.14	21	2.14	24	1.71	20	1.29	15
Generation	2.47	38	2.26	32	1.37	41	1.21	38	1.26	40
Transmission	4.00	7	5.00	7	2.00	6	1.00	3	1.00	3
Total	2.86	100	3.16	100	1.47	100	1.42	100	1.40	100
Brown Coal										
Mining	2.82	32	2.64	26	1.00	19	1.18	25	1.36	31
Transport	3.83	23	4.00	21	3.00	32	2.00	23	1.00	12
Generation	1.64	37	2.23	44	1.09	42	1.14	48	1.18	53
Transmission	4.00	8	5.00	9	2.00	7	1.00	4	1.00	4
Total	2.39	100	2.73	100	1.39	100	1.27	100	1.20	100

Table 7: Qualitative uncertainty scores calculated using the Rousseaux et al. method

Parameter	Acceptability at Objective Quality Score				Variability
	1	2	3	4	
Black Coal					
Reliability	0.0	51.2	76.7	86.0	40.9
Completeness	0.0	48.8	62.8	72.1	54.1
Temporal	79.1	86.0	93.0	95.3	75.9
Geographical	74.4	86.0	97.7	100	44.4
Technological	81.4	81.4	97.7	100	51.7
Brown Coal					
Reliability	36.6	61.0	73.2	90.2	81.3
Completeness	2.4	68.3	78.0	78.0	58.6
Temporal	85.4	90.2	92.7	92.7	85.9
Geographical	80.5	92.7	100	100	27.7
Technological	90.2	90.2	100	100	30.2

contribution to environmental impacts[6], and thus also cannot be used to discuss the quality of impact results.

3.3 Combined uncertainty

Combined uncertainty measures for the black and brown coal systems were obtained using the methods of Kennedy et al. and Meier, using the indicators shown in Table 1. Presented in **Table 8** are those values obtained for climate change, along with the numerical simulation results reported in Table 4. For the black coal system, the use of the Kennedy et al. method modified the mean value by a small amount (± 5%), while increasing the standard deviation (and hence uncertainty) by 40–90%. The use of the Meier method had little effect on either the mean or the standard deviation. For the brown coal system, both methods left the mean unchanged, while increasing the standard deviation dramatically. In fact, the standard deviations of the Kennedy et al. brown coal systems were very similar to those of the black coal system, although still lower as a percentage of the mean values. Therefore, it was clear that the brown coal system had lower uncertainty than the black coal system. The two methods produce very different results, and there was no evidence that either approach produced results that were more accurate, or more representative of qualitative uncertainty, than the other. More importantly, it could not be demonstrated that either method produced a measure of uncertainty that was more relevant than that of the numerical uncertainty method alone.

[6] The method of Lindeijer et al.[1] is reported to do this, however it is only available in Dutch.

Table 8: Variation from numerical analysis values using the methods of Kennedy at al. and Meier (SD = Standard Deviation)

Distribution	Method	Climate Change ($kg_{CO_2\text{-eq.}}$ per MWh)			
		Black Coal		Brown Coal	
		Mean	SD	Mean	SD
Triangle	Numerical	1082	309	1319	102
	Kennedy et al.	1062	545	1355	558
	Meier	1059	331	1367	158
Uniform	Numerical	1080	460	1386	138
	Kennedy et al.	1087	663	1423	550
	Meier	1108	495	1393	230
Normal	Numerical	1038	255	1338	76
	Kennedy et al.	1027	478	1354	551
	Meier	1021	259	1342	135
Lognormal	Numerical	1099	334	1346	76
	Kennedy et al.	1102	572	1331	524
	Meier	1074	332	1353	139

Table 9: Differential numerical uncertainty ranges (brown coal – black coal, per MWh)

System	Probability Distribution Type	Climate Change ($kg_{CO_2\text{-eq.}}$)		Acidification ($kg_{SO_2\text{-eq.}}$)		Resource Depletion ($kg_{Sb\text{-eq.}}$)	
		Mean	SD	Mean	SD	Mean	SD
Black Coal – Brown Coal	Average	301	–	–3.30	–	4.54	–
	Triangular	237	321	4.02	6.60	4.55	2.05
	Uniform	306	484	10.0	9.2	6.77	2.8
	Normal	300	267	–3.53	5.05	4.52	1.62
	Log Normal	247	341	–2.46	4.57	4.15	2.21

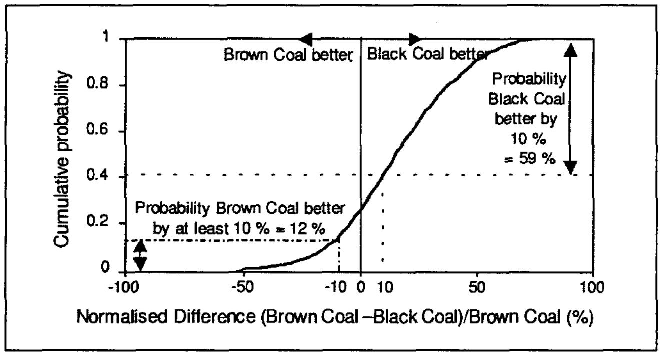


Fig. 6: Cumulative distribution function of the normalised difference

3.4 Comparisons

The differential case (brown coal system minus black coal system) was also calculated (**Table 9**) to determine which system had least environmental impact. While the average values indicated that the black coal system had lower climate change and resource depletion impacts and higher acidification impact, the numerical ranges overlapped indicating that these outcomes were not certain. Therefore, clear conclusions could not be derived from this method.

A normalised difference probability distribution plot was produced for the triangular climate change impact, calculated as (brown coal-black coal)/brown coal (**Fig. 6**). This figure showed that there was a 12% chance that the brown coal system was at least 10% better than the black coal system, while there was a (100-41) or 59% chance that the black coal system was 10% better than the brown coal system. Thus, it could be concluded that the black coal system was more likely to produce a better result, as predicted by the averages. Thus, a clearer picture of the differences between the systems and the potential for error was obtained.

4 Conclusions

Data quality assessment is important for the development and acceptance of LCA as a decision-making tool. Yet, data quality assessment is rarely performed, and there is no consensus on the methods to use. Methods for data quality assessment have recently undergone considerable development. However, increased demands on resources required for their implementation and doubts about resulting benefits have impeded adoption of any of the methods. Further, a defined means of reporting conclusions from uncertainty assessments in LCA, essential for comparing results from different studies, remains to be elucidated.

Six different methods of assessing quantitative and qualitative uncertainty have been used in a case study of electric power generation from Australian black coal and brown coal. Each method indicated higher uncertainty in the black coal system results than in the brown coal system results. The qualitative methods enabled the source of this difference to be traced to the greater usage of data derived from plant measurements for the brown coal case.

The numerical methods enabled a single uncertainty range to be reported for each environmental impact result, allowing the LCA results to be presented using standard quality assessment tools (i.e. box plots). The qualitative methods also presented significant data quality information, and allowed the identification of both the source and type of deficiencies in data quality. The methods which combine qualitative uncertainty with quantitative uncertainty to provide quantitative outputs were not recommended. They were reliant on subjective (expert) reasoning, provided no greater information than the quantitative methods, and presented far less information than if the qualitative and quantitative methods were presented separately.

The impacts calculated using average values of input data showed that the brown coal system had greater climate change and resource depletion impact scores, but a lower acidification impact score than the black coal system. However, as the uncertainty ranges overlapped for each impact, it was shown that it is possible under certain circumstances for these relativities to be reversed. For example, if a black coal system operates at low efficiency, its climate change and resource depletion impacts can be greater than for a brown coal system, producing an equivalent amount of electricity, but operating at high efficiency. The normalised difference method was able to show, in an objective manner, that for the climate change impact, the black coal system has a greater probability of a lower impact result than the brown coal system.

Therefore, it is recommended that impact results should be expressed using the results of a quantitative assessment, using a skewed probability distribution (e.g. triangular or log

normal), supported by the qualitative assessment of Wrisberg. When the uncertainty ranges of impact results overlap, the normalised difference method should be used to rank the different options.

As the data quality assessment methods are still underdeveloped, a quality analysis is recommended only where the relative merits of options are debatable and the magnitudes of long-term environmental and economic impacts are considerable.

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