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LCA Methodology

Numerical Approaches to Life Cycle Interpretation

The case of the ecoinvent'96 database

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Abstract

Goal, Scope and Background. To strengthen the evaluative power of LCA, life cycle interpretation should be further developed. A previous contribution (Heijungs & Kleijn 2001) elaborated five examples of concrete methods within the subset of numerical approaches towards interpretation. These methods were: contribution analysis, perturbation analysis, uncertainty analysis, comparative analysis, and discernibility analysis. Developments in software have enabled the possibility to apply the five example methods to explore the much-used ecoinvent'96 database.

Discussion of Methods. The numerical approaches implemented in this study include contribution analysis, perturbation analysis, uncertainty analysis, comparative analysis, discernibility analysis and the newly developed key issue analysis. The data used comes from a very large process database: ecoinvent'96, containing 1163 processes, 1181 economic flows and 571 environmental flows.

Conclusions. Results are twofold: they serve as a benchmark to the usefulness and feasibility of these numerical approaches, and they shed light on the question of stability and structure in an often-used large system of interconnected processes. Most of the approaches perform quite well: computation time on a moderate PC is between a few seconds and a few minutes. Only Monte Carlo analyses may require much longer, but even then it appears that most questions can be answered within a few hours. Moreover, analytical expressions for error propagation are much faster than Monte Carlo analyses, while providing almost identical results. Despite the fact that many processes are connected to each other, leading to the possibility of a very unstable system and very sensitive coefficients, the overall results show that most results are not extremely uncertain. There are, however, some exceptions to this positive message.

Keywords: Contribution analysis; discernibility analysis; ecoinvent'96; key issue analysis; life cycle interpretation; perturbation analysis; sensitivity analysis; uncertainty analysis

1 Goal, Scope and Background

Part of the ISO 14043 definition of life cycle interpretation is in terms of the analysis of results from inventory analysis and/or impact assessment (Anonymous 2000). To this aim, three elements are distinguished:

- Identification of significant issues based on the results of the LCI and LCIA phases of LCA,
- evaluation which considers completeness, sensitivity and consistency checks,
- conclusions, recommendations and reporting.

As LCA is a tool for evaluation and to support decisions, it is clear that interpretation is in some respect a crucial phase of LCA. It is therefore necessary that sound procedures and powerful methods are available to support the interpretation phase.

Obviously, the approaches mentioned in ISO 14043 require a quite diverse type of activity, expertise, and method. Sensitivity checks belong to the domain of statistical processing, whereas reporting requires communicational skills. In a previous contribution (Heijungs & Kleijn 2001), we proposed to distinguish procedural and numerical approaches to life cycle interpretation, and elaborated five examples of concrete methods within the subset of numerical approaches. These methods were:

- contribution analysis,
- perturbation analysis,
- uncertainty analysis,
- comparative analysis,
- discernibility analysis.

They were implemented in the educational software tool, Chain Management by Life Cycle Assessment (CMLCA <http://www.leidenuniv.nl/cml/ssp/software/cmlca>), and examples of their use for a fictitional case study were presented. In the meantime, CMLCA has evolved in such a way that it is able to handle very large systems, and an import facility for the ecoinvent'96 database (3rd edition, Frischknecht et al. 1996) has been created. This means that the practicality of the five example methods can be submitted to a test for large systems and, at the same time, that the much-used ecoinvent'96 database can be submitted to a number of potentially useful approaches in life cycle interpretation. The present paper describes such an analysis.

Meanwhile, the numerical approaches towards interpretation have developed further as well. Heijungs & Suh (2002) introduce two more methods that can be classified as a way of interpretation:

- key issue analysis,
- structural analysis.

These have also been implemented in CMLCA, and this paper also describes how the key issue analysis performs on the ecoinvent'96 system, and conversely how the ecoinvent'96 system performs on this test. The structural analysis is left out of this paper because it is still in a too early stage of development. For similar reasons, another newly developed approach, structural path analysis (Treloar 1997, Suh 2003), which is a method to disentangle important pathways in a network of unit processes, has not yet been included in this paper. A development that has been included is that matrix perturbation theory has provided analytical methods for uncertainty analysis (Heijungs & Suh 2002, Heijungs 2002), which may re-

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place the Monte Carlo-based numerical approaches. As we will see in a next section, an analytical method may well be superior to a numerical method with respect to speed of computation without being worse in other respects.

This paper can be considered as a sequel to our earlier one (Heijungs & Kleijn 2001). We will largely follow the structure of that paper. As before, the CMLCA program can be downloaded to verify and expand on our results. Notice, however, that the data used is not provided by us, because they are the property of the publishers of ecoinvent'96. If you possess the original CD, entitled 'Ökoinventare von Energiesystemen. 3. Edition', you can redo our analyses. We have translated the German names of processes, flows and compartments into English. The original German names have been added for easy reference in the Appendix to this article. It should be mentioned that a new release of the ecoinvent database has become available, ecoinvent data v1.01, also referred to as ecoinvent 2000 <http://www.ecoinvent.ch>. The timing and its price determined that we used the 3rd edition of the ecoinvent'96 for our analysis. In principle, the procedures should work in the same way. Computation requirements may be higher due to the larger size of the matrices.[1]

Some of the methods for interpretation require a specification of the uncertainties of the data, such as the probability distribution function with a characteristic, e.g. a normal distribution with a mean of 100 kg CO_2 and a standard deviation of 3 kg CO_2. These data are not available for ecoinvent'96. As a solution, we have, where required, introduced a normal distribution[2] with the given number as mean and a standard deviation of 5% of that value (hence, a variation coefficient of 0.05).

All methods can be used at different levels of analysis, viz. inventory analysis, characterisation, normalisation and weighting. To concentrate on the ecoinvent database, the discussion is restricted to the inventory analysis. The generalisation to higher levels of analysis is, however, straightforward. Computation times may be longer, of course, and some of the results may be quite uncertain because the impact assessment data introduce additional uncertainties.

An important part of the performance aspect is of course the computer time requirements. For each of the methods described, we will give approximate computation times, found on a computer that could now be described as old-fashioned: Pentium III, 667 MHz, 128 MB RAM. With an optimized state-of-the-art computer, it should be possible to find much smaller computation times. Before turning to the interpretation-oriented methods, we should say something on the preparatory work that is done by CMLCA. Depending on the exact route, several intermediate results are calculated and stored for future reference. These are:

- the inverse of the technology matrix, $\mathbf{A}^{-1}$ (see Heijungs & Suh 2002, p.17), of which the computation takes 120 seconds,
- the intensity matrix $\mathbf{\Lambda}$ (see Heijungs & Suh 2002, p. 19), of which the computation takes about 140 seconds (provided $\mathbf{A}^{-1}$ is available),
- two matrices with the variances of the process data.

When these matrices have been calculated and are thereby available, most methods for interpretation run smoothly. All timing details given are based on the assumption that these intermediate results have already been calculated.

Hereafter, we will discuss all methods for interpretation that we have tried. Each method is described in a separate section. The description of each method that has been discussed by Heijungs & Kleijn (2001) is divided into the following subsections:

- introduction; review of the basic concept,
- results for ecoinvent'96,
- performance.

The key issue analysis, which has not been discussed by Heijungs & Kleijn (2001), receives a more extensive description. The paper concludes with a discussion of the results of the interpretation of the ecoinvent'96 database and a reflection on the role and future of life cycle interpretation.

2 Discussion of Methods

2.1 Contribution analysis

The contribution analysis decomposes the aggregated results of inventory analysis, characterisation, normalisation or weighting into a number of constituting elements. For the inventory analysis, this means that a certain inventory item, e.g. the system-wide carbon dioxide emission, is traced back to the share that the different unit processes in the system are responsible for.

2.1.1 Results for ecoinvent'96

With a reference flow of 1 TJ UCPTE electricity, a contribution analysis of atmospheric carbon dioxide is shown in **Table 1**. It is immediately clear that only a few processes are responsible

[1] During the review and revision period of this paper, the ecoinvent v1.01 has become public, and an interface has been added to CMLCA. To give an impression: solving a system of 2522 processes and flows requires a few minutes.

[2] Of course, the validity of the assumption of normality and the value of 5% may be discussed in itself. This is, however, outside the scope of the present paper.

Table 1: Contribution analysis for carbon dioxide (to air) ([E25] as shown in CMLCA) associated with the functional unit 1 TJ UCPTE electricity ([G181] Strom-Mix UCPTE). Contributions below 3% are not shown; this explains that the entries shown add up to 79% of the system-wide release only

Process	Value (kg)	Contribution (%)
[P522] lignite power plant (Germany)	2.87E4	21
[P580] coal power plant (Germany)	2.3E4	17
[P400] oil thermic electricity (Italy)	1.28E4	9
[P509] electricity from gas power plant (Italy)	9.06E3	7
[P581] coal power plant (Spain)	8E3	6
[P526] lignite power plant (Greece)	6.03E3	4
[P511] electricity from gas power plant (Netherlands)	4.68E3	3
[P513] electricity from gas power plant (West Germany)	4.43E3	3
[P583] coal power plant (France)	4.47E3	3
[P584] coal power plant (Italy)	3.69E3	3
[P585] coal power plant (Netherlands)	3.65E3	3

for a large part of this emission. In this case, the emissions from coal combustion in Germany are seen to contribute to almost 40% of the system-wide CO_2 emission of UCPTE electricity.

2.1.2 Performance

With the aggregated inventory results available, a contribution analysis for ecoinvent is ready within less than one second.

2.2 Perturbation analysis

The perturbation analysis identifies sensitive parameters, i.e. input parameters of which a small change induces a large change in a selected result. For instance, one may try to find out a process for which data a small change in data will lead to a large change in the carbon dioxide emission. The factor that couples a small change in input to a change in output is referred to as the multiplier. Multipliers larger than 1 (or smaller than –1) indicate sensitive parameters, while multipliers close to 0 indicate insensitive parameters. The rationale for using a perturbation analysis instead or on top of an uncertainty analysis is that it allows the researcher to study inherent sensitivities, even for variables for which no uncertainty indication is known.

2.2.1 Results for ecoinvent'96

Again, a reference flow of 1 TJ UCPTE electricity was chosen, as well as the target flow of atmospheric carbon dioxide. Results are shown in Table 2. Here, we see that most parameters of the system have a very small influence on the carbon dioxide emission. There is only one sensitive parameter (directly related to the electricity mixing process), and almost all multipliers are between –0.25 and 0.25. There are two multipliers in the intermediate region, around ±0.4; these relate to the share of German electricity in the UCPTE mix.

CMLCA also allows one to run the perturbation analysis for all environmental flows in one step. This yields a very long table, of which we have brought only a small part into this paper (**Table 3**). In Table 3, the first column indicates the environmental flow that is perturbed as the result of a deliberate perturbation of the coefficient relating to the process in column 2 and the flow (often economic, but sometimes environmental) in column 3. One sees that waste heat (to water) has many large coefficients, some of which are even larger than 100. A multiplier of 30 means that a modest input uncertainty of 3% would propagate as an output uncertainty of about 100%, and a multiplier of 100 would propagate a 1% uncertainty as 100%. Suspended particles (to water) is the next sensitive substance, with multipliers

Table 2: Perturbation analysis for carbon dioxide (to air) ([E25] in CMLCA) associated with the functional unit 1 TJ UCPTE electricity ([G181] in CMLCA). Multipliers between –0.1 and 0.1 (many) are not shown

Process	Economic/environmental flow	Multiplier
[P293] electricity (UCPTE mix)	[G181] electricity (UCPTE mix)	–1.02
[P294] electricity (West Germany mix)	[G182] electricity (West Germany)	–0.434
[P293] electricity (UCPTE mix)	[G182] electricity (West Germany)	0.433
[P589] electricity from lignite power plant (Germany)	[G236] electricity from lignite power plant (Germany)	–0.213
[P294] electricity (West Germany mix)	[G236] electricity from lignite power plant (Germany)	0.211
[P522] lignite power plant (Germany)	[G626] lignite power plant (Germany)	–0.211
[P589] electricity from lignite power plant (Germany)	[G626] lignite power plant (Germany)	0.211
[P522] lignite power plant (Germany)	[E25] carbon dioxide (to air)	0.21
[P285] electricity (Italy mix)	[G173] electricity (Italy mix)	–0.209
[P293] electricity (UCPTE mix)	[G173] electricity (Italy mix)	0.209
[P597] electricity from coal power plant (Germany	[G414] electricity from coal power plant (Germany)	–0.175
[P294] electricity (West Germany mix)	[G414] electricity from coal power plant (Germany)	0.171
[P580] coal power plant (Germany)	[G666] coal power plant (Germany)	–0.17
[P597] electricity from coal power plant (Germany	[G666] coal power plant (Germany)	0.17
[P580] coal power plant (Germany)	[E25] carbon dioxide (to air)	0.168
[P400] oil thermic electricity (Italy)	[G390] oil thermic electricity (Italy)	–0.111
[P285] electricity (Italy mix)	[G390] oil thermic electricity (Italy)	0.109

Table 3: Perturbation analysis for all environmental flows associated with the functional unit 1 TJ UCPTE electricity ([G181] Strom-Mix UCPTE). Most multipliers between –100 and 100 are not shown

Environmental flow	Process	Economic/environmental flow	Multiplier
[E142] waste heat (to water)	[P690] water flow power plant (UCPTE)	[G753] water flow power plant (UCPTE)	–128
[E142] waste heat (to water)	[P690] water flow power plant (UCPTE)	[E142] waste heat (to water)	128
[E142] waste heat (to water)	[P692] water barrage power plant (UCPTE)	[G755] water barrage power plant (UCPTE)	–110
[E142] waste heat (to water)	[P293] electricity (UCPTE mix)	[G182] electricity (West Germany)	–106
[E142] waste heat (to water)	[P294] electricity (West Germany mix)	[G182] electricity (West Germany)	106
[E142] waste heat (to water)	[P692] water barrage power plant (UCPTE)	[E142] waste heat (to water)	105
Many more multipliers for [E142] waste heat (to water)			
[E455] suspended particles (to water)	[P218] decarbonized water	[W340] residue decarbonization in storage	–15.7
[E455] suspended particles (to water)	[P922] residue decarbonization in storage	[W340] residue decarbonization in storage	15.7

around 15. Thus, the really problematic sensitivities are easily identified with the perturbation analysis, even if the exact uncertainty details of the process data are unknown. Far much lower on the list (not shown in the Table 3) are ethylene oxide to air, acenaphtene to water and acrilonitrile to water, with multipliers between ±4 and ±5. But, as we have seen in Table 2, there are also environmental flows (CO_2 in this case) that do not occur in this high sensitivity table and that have multipliers between –0.1 and 0.1.

2.2.2 Performance

Heijungs & Kleijn (2001) speculated that a numerical variation as a way to address the perturbation analysis would be quite problematic for large systems. This is confirmed by our analysis. The ecoinvent data contains approximately 9000 nonzero entries, and a successive variation of each of these parameters with a solution to the system requires some 300 hours. For the analytical approach (cf. Sakai & Yokoyama 2002), however, we are now much more optimistic. The perturbation analysis for CO_2 (see Table 2) requires not more than 20 seconds, and an automated run for all environmental flows (see Table 3) is completed within 5 min. This means that within a few minutes one can have a full analysis of the sensitivity of the ecoinvent for a chosen reference flow. For a different reference flow, the analysis must be carried out anew.

2.3 Uncertainty analysis

The uncertainty analysis is devoted to the systematic study of the propagation of input uncertainties into output uncertainties. If uncertainties of the process data are specified, for instance in the form of a Gaussian distribution with a certain standard deviation that may differ per process data item, the uncertainty analysis will produce standard deviations or confidence intervals for the inventory results.

There are two basic ways of running an uncertainty analysis: by random sampling and by analytical formulas for error propagation. A well-known form of random sampling is the Monte Carlo analysis, of which the basic procedure is as follows:

- every input parameter is considered as a stochastic variable with a specified probability distribution,
- the LCA-model is constructed with one particular realisation of every stochastic parameter,
- the LCA-results are calculated with this particular realisation,
- the previous two steps are repeated a number of times (the sample size N),
- the sample of LCA-results is investigated as to its statistical properties (such as the mean, the standard deviation, the confidence interval).

There are various extensions to this basic setup of Monte Carlo analysis, known under names like Latin hypercube sampling and the Metropolis algorithm; see Morgan & Henrion (1990) and especially Liu (2003) for an extended discussion.

The analytical approach starts from the idea that the influence of perturbations may be approximated by differential calculus, and that the variances due to independent stochastic perturbations are additive. For instance, when a mathematical relationship is specified as

$$z = f(x, y)$$

then, the variance of z is approximately

$$\mathrm{var}(z) = \left(\frac{\partial f}{\partial x}\right)^2 \mathrm{var}(x) + \left(\frac{\partial f}{\partial y}\right)^2 \mathrm{var}(y)$$

Explicit matrix equations for LCA enable a similar elaboration of the variance of LCA-results (see Heijungs & Suh 2002, p. 140 ff). It is noteworthy (cf. Maurice et al. 2000) that the analytical approach does not require that the form of the probability distribution of the input parameters be specified. It suffices to specify the first two moments (mean and variance). Thus, the data requirements of an analytical approach are lower than those of a sampling approach.

2.3.1 Results for ecoinvent'96

Input uncertainties are not available for ecoinvent. We have assumed that all process data are characterised by a Gaussian distribution with a standard deviation that is 5% of the baseline value. Thus, if a certain input data item was specified as 200 kg, we replace it by N(200, 10), meaning a normal distribution with a mean of 200 kg and a standard deviation of 10 kg. Of course, one may dispute the validity of this Gaussian assumption of 5%, especially as the default distribution for ecoinvent data v1.01 is lognormal (cf. Hofstetter 1998). Such discussions are outside the scope of this paper, which concentrates on a mere demonstration of how assumed uncertainties propagate.

With 100 Monte Carlo runs, the reference flow 1 TJ UCPTE electricity yielded results for carbon dioxide and some other flows as seen in **Table 4**. Here, baseline indicates the result without stochastic calculations, while mean refers to the average result of the 100 Monte Carlo results. The column labeled Variation gives the coefficient of variation, the dimensionless ratio between the sample standard deviation and the mean; here it has been expressed as a percentage. In general, baseline and mean value agree well, and the agreement will increase when the number of Monte Carlo runs increases. For those inventory items for which the coefficient of variation is very large, there may be quite some discrepancy between baseline and mean. This is an artifact of a small sample size: one cannot expect to cover the parameter range well with 100 runs if it is very large. Observe that for some flows (like HFC-134a to air and styrene to air) the two results do not agree in sign. This is also a clear sign of numerical instabilities and/or exceptionally large variation.

We see that, although all input parameters in a very large and interconnected system have an uncertainty of 5%, the CO_2-results have an uncertainty that is still surprisingly small (7%). It is also clear that the quite modest output uncertainties for CO_2 are not exceptional. Indeed, almost all output uncertainties are to be found somewhere between 7 and 15%. There are, however, a few environmental flows which have a much larger uncertainty. This is the case for the parameters that were identified as sensitive in the perturbation analysis, most notably waste heat to water. Output uncertainties can be as large as a few thousand %, which provides serious doubts on the validity of decisions that are (partly) based on such highly sensitive flows.

Table 4: Uncertainty analysis (on the basis of 100 Monte Carlo runs and on the basis of analytical formulas for error propagation) for a selected number of environmental flows associated with the functional unit of 1 TJ UCPTE electricity ([G181] Strom-Mix UCPTE)

Environmental flow	Baseline	Mean (Monte Carlo)	Variation (Monte Carlo; %)	Variation (analytical; %)	Unit
[E20] cadmium (to air)	0.00293	0.003	8	7	kg
[E21] methane (to air)	253	262	12	12	kg
[E22] cyanide (to air)	0.00016	0.000164	11	11	kg
[E23] cobalt (to air)	0.0175	0.018	9	8	kg
[E24] carbon monoxide (to air)	33.4	34.2	7	7	kg
[E25] carbon dioxide (to air)	1.37E5	1.39E5	7	7	kg
[E26] chromium (to air)	0.0136	0.0139	7	7	kg
[E27] copper (to air)	0.0374	0.0384	7	7	kg
[E28] ethane (to air)	1.2	1.22	9	9	kg
[E29] ethylene (to air)	0.129	0.133	9	9	kg
[E30] acetylene (to air)	0.00217	0.00224	11	10	kg
[E31] iron (to air)	1.51	1.53	8	8	kg
[E32] hydrogen sulfide (to air)	0.133	0.136	12	12	kg
[E33] mercury (to air)	0.00807	0.00823	8	7	kg
[E134] HFC-134a (to air)	–1.17E-6	8.87E-8	5057	15	kg
[E135] HCFC-22 (to air)	0.000222	0.000228	14	13	kg
[E136] styrene (to air)	1.49E-10	–5.55E-12	2597	22	kg
[E137] dioxin/TEQ (to air)	5.43E3	5.54E3	8	8	ng
[E138] carbon tetrachloride (to air)	2.9E-5	2.98E-5	10	9	kg
[E139] chloroform (to air)	1.34E-6	1.42E-6	17	13	kg
[E140] vinyl chloride (to air)	8.28E-6	8.64E-6	15	12	kg
[E141] xylene (to air)	0.858	0.878	8	8	kg
[E142] waste heat (to water)	–0.000569	–0.000684	1771	2052	TJ
[E143] acenaphthene (to water)	–1.25E-16	9.64E-17	462	41	kg
[E144] acenaphthylene (to water)	0.00785	0.008	12	12	kg
[E145] acrilonitrile (to water)	–1.19E-13	9.18E-14	458	41	kg
[E146] bis(2-ethylhexyl) phthalate (to water)	3.02E-9	3.14E-9	13	11	kg
[E147] BOD5 (to water)	0.0766	0.079	9	9	kg
[E148] butyl benzyl phthalate (to water)	6.46E-14	–1.64E-15	3794	22	kg
[E149] 1,1,1-trichlorethane (to water)	9.22E-8	9.7E-8	13	13	kg

Table 4 also shows results for the analytical approach. The standard deviation is the square root of the analytically determined variance. Observe that no separate mean value can be calculated here. The coefficient of variation is the ratio between standard deviation and baseline result.

The agreement between sampling approach and analytical approach is quite good, although each series of Monte Carlo trials has a random character, and the analytical approach is a first-order approximation only. For inventory items with a large coefficient of variation the agreement is bad, although both approaches tell us that the variation is large. It is difficult to tell which of the two approaches produces more correct results in this case. The sampling approach may need an excessively large number of Monte Carlo runs (or a better strategy to cover sparsely populated regions of sample space), while the analytical approach may need to take more that just the first two moments into account, as the first-order approximation may no longer be sufficient. Using the baseline instead of the sample mean for determining the coefficient of variation in the sampling approach may already provide an improvement. There are a few flows (like the CFC 134a) for which the analytical method suggests a rather small uncertainty (15%), where the sampling approach yields a huge uncertainty (5057%). We speculate that one outlier of the Monte Carlo sampling might be responsible for this.

2.3.2 Performance

One Monte Carlo run for the ecoinvent requires approximately 30 seconds. An experiment with 100 runs thus requires somewhat less than one hour. This is feasible, but not very practical. And the number of Monte Carlo runs is typically set higher, e.g. to 500 or 1000. With our old-fashioned computer and the probably suboptimal algorithm in CMLCA, this would require a full working day. Increased computer performance and smarter algorithms may decrease the computer time substantially. Indeed, we redid the calculations on a 2.4 GHz PC with 18 seconds per Monte Carlo run.

Far more promising, however, is the analytical approach to uncertainty analysis. CMLCA is able to carry it out in a few minutes time. Faster computers and more efficient coding may reduce this to a minute or so.

2.4 Comparative analysis

The comparative analysis is nothing more than a systematic place to simultaneously list the LCA results for different product alternatives.

Table 5: Comparative analysis for carbon dioxide (to air) ([E25 in CMLCA) associated with several alternative national electricity scenarios, corresponding to functional unit 1 TJ electricity. The UCPTE alternative has been set to 1

A	B	CH	E	Ex-Ju	F	GR	I	L	NL	P	UCPTE	W-D
0.51	0.88	0.038	1.01	0.96	0.24	2.51	1.56	3.94	1.44	1.3	1	1.43

2.4.1 Results for ecoinvent'96

Table 5 shows a tabular representation of the comparative analysis of 1 TJ electricity according to several national characteristics (Austria, Belgium, Switzerland, Spain, former Yugoslavia, France, Greece, Italy, Luxembourg, Netherlands, Portugal, UCPTE, and Western Germany) for CO_2. We see that there are quite some differences between Switzerland and Luxembourg, but that the difference between the Netherlands and Western Germany is very small. Note, however, that this size of the difference does not say anything to the significance of these differences. The section on discernibility analysis below will address the issue of significance.

2.4.2 Performance

Once the inverse technology matrix is available, CMLCA calculates the comparative analysis within a few seconds.

2.5 Discernibility analysis

The discernibility analysis combines the comparative analysis and the uncertainty analysis. It is based on comparing the product alternatives for a large number of Monte Carlo runs. In contrast to the uncertainty analysis, no analytical approach is available, at least not now, and probably never. Heijungs & Kleijn (2001) proposed a pure ranking-based comparative analysis (based on rank-order statistics), but it can in principle be applied to the proper values as well. Thus, we may compute the LCA-results for the different product alternatives per Monte Carlo run, and apply a *t*-test comparison among each pair of product alternatives. Or we may determine the rank order of each product alternative per Monte Carlo run, and count the frequency of pair-wise preference.

2.5.1 Results for ecoinvent'96

As in the uncertainty analysis, it was assumed that all process data is associated with a Gaussian uncertainty of with a standard deviation of 5%. A Monte Carlo analysis of 100 runs gives results for CO_2 as in **Table 6**. We see, for instance, that Austrian electricity (A) is discernible from all other national electricities, better than most, worse than Swiss (CH) and French (F) electricity on CO_2. Spanish electricity (E), however, is far less discernible. Its CO_2 is not significantly different from that of Belgium (B), former Yugoslavia (Ex-Ju) and UCPTE. The reader should observe that the results for Belgium and Spain are not significantly different, whereas a purely non-stochastic comparison (see Table 5) yields quite some difference between the two (0.88 and 1.01, respectively). This is an illustration of the fact that a large difference is not always a significant difference. The difference between Portugal and Italy is on the same order of magnitude (1.3 versus 1.56) while being significant at the 97%-level.

Values and 95%-confidence intervals of the different alternatives can be displayed in a simple graph (**Fig. 1**). Observe here that the third and sixth bar from the right, Portugal and Italy, show quite some overlap of confidence interval, while the run-by-run ranking shows that Portugal beats Italy 97 out of 100 times.

2.5.2 Performance

As for the uncertainty analysis, one Monte Carlo run takes approximately 30 seconds, hence a good analysis requires several hours. However, in contrast to the uncertainty analysis, no time-saving analytical approach is available at this moment.

Table 6: Discernibility analysis for carbon dioxide (to air) ([E25] in CMLCA) associated with several alternative national electricity scenarios, corresponding to functional unit 1 TJ electricity. All data uncertainties have been assumed to be drawn from a Gaussian distribution with a standard deviation of 5%. The number of Monte Carlo runs is 100. The number 0.83 at the intersection of row 5 (E) and column 3 (B), for instance, indicates that E had a higher CO_2-emission than B in 83% of the Monte Carlo runs. The asterisks indicate the conventional significance statistic: * means that $p<0.05$, ** that $p<0.01$, and *** that $p<0.001$

R>C	A	B	CH	E	Ex-Ju	F	GR	I	L	NL	P	UCPTE	W-D
A	–	0^{***}	1	0^{***}	0^{***}	1	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}
B	1	–	1	0.17	0.24	1	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0.12	0^{***}
CH	0^{***}	0^{***}	–	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}
E	1	0.83	1	–	0.64	1	0^{***}	0^{***}	0^{***}	0^{***}	0.03^{*}	0.45	0^{***}
Ex-Ju	1	0.76	1	0.36	–	1	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0.34	0^{***}
F	0^{***}	0^{***}	1	0^{***}	0^{***}	–	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}
GR	1	1	1	1	1	1	–	1	0^{***}	1	1	1	1
I	1	1	1	1	1	1	0^{***}	–	0^{***}	0.79	0.97	1	0.8
L	1	1	1	1	1	1	1	1	–	1	1	1	1
NL	1	1	1	1	1	1	0^{***}	0.21	0^{***}	–	0.84	1	0.6
P	1	1	1	0.97	1	1	0^{***}	0.03^{*}	0^{***}	0.16	–	0.99	0.23
UCPTE	1	0.88	1	0.55	0.66	1	0^{***}	0^{***}	0^{***}	0^{***}	0.01^{**}	–	0^{***}
W-D	1	1	1	1	1	1	0^{***}	0.2	0^{***}	0.4	0.77	1	–

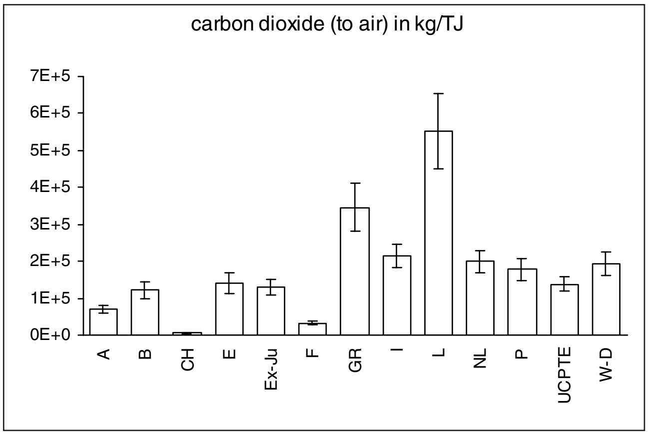

Fig. 1: Visualization of the 95%-confidence intervals for carbon dioxide (to air) ([E25] in CMLCA) associated with several alternative national electricity scenarios (from left to right Austria, Belgium, Switzerland, Spain, Former Yugoslavia, France, Greece, Italy, Luxembourg, Netherlands, Portugal, UCPTE, and Western Germany), corresponding to functional unit 1 TJ electricity. All data uncertainties have been assumed to be drawn from a Gaussian distribution with a standard deviation of 5%. The number of Monte Carlo runs is 100.

2.6 Key issue analysis

The key issue analysis is not included by Heijungs & Kleijn (2001). It is discussed in more detail than the other methods.

2.6.1 Basic concept

The key issue analysis has been introduced earlier (Heijungs 1996) and reappears in Heijungs & Suh (2002). The basic idea is that not only LCA results can be decomposed in a contribution analysis, but that the uncertainty of LCA results can be decomposed as well. This is especially useful in an iterative LCA setup, where results of the key issue analysis direct the researcher's focus on those data items for which more accurate data should be gathered with priority. Perhaps confusingly, this type of analysis is sometimes referred to as sensitivity analysis (Saltelli et al. 2001).

The key issue analysis is based on the additive property of variances in the analytical approach towards the uncertainty analysis. If, according to the equation in **Section 2.3**,

$$\mathrm{var}(z) = \left(\frac{\partial f}{\partial x}\right)^2 \mathrm{var}(x) + \left(\frac{\partial f}{\partial y}\right)^2 \mathrm{var}(y)$$

then one may decompose the resulting variance into two contributions:

$$\mathrm{var}(z) = \mathrm{var}(z)_x + \mathrm{var}(z)_y$$

where

$$\mathrm{var}(z)_x = \left(\frac{\partial f}{\partial x}\right)^2 \mathrm{var}(x)$$

and

$$\mathrm{var}(z)_y = \left(\frac{\partial f}{\partial y}\right)^2 \mathrm{var}(y)$$

Thus, one may express the relative contribution of the uncertainty in x to the uncertainty in z as $\mathrm{var}(z)/\mathrm{var}(z)_x$, and the relative contribution of the uncertainty in y to the uncertainty in z as $\mathrm{var}(z)/\mathrm{var}(z)_y$.

The analytical formulas for LCA are provided by Heijungs & Suh (2002). Calculating the derivatives requires some straightforward calculus, and again leads to explicit formulas, that may be implemented in software for LCA.

2.6.2 Possibilities

Like the uncertainty analysis, the key issue analysis can be performed at the levels of inventory analysis, characterisation, normalisation and weighting. Of course, as the level of aggregation progresses, so does the number of input data items, and hence the number of uncertain input data items.

Although the key issue analysis resembles the contribution analysis, the types of directions for decomposition differ. In a contribution analysis, one can ask what is the contribution to the weighted index of SO_2 from electricity production by way of acidification. In a key issue analysis, one can ask what the contribution to the uncertainty of the weighted index is of the uncertainty in the SO_2 emission of electricity production, or of all the SO_2 emissions, or of all the unit processes, or of the SO_2 acidification factor, or of all the SO_2 characterisation factors, or of all the acidification factors.

2.6.3 Tabular and graphical representation

The tabular and graphical representations of the results of a key issue analysis is the same as that for a contribution analysis (cf. Heijungs & Kleijn 2001).

2.6.4 Restrictions and warnings

For the contribution analysis, there were problems in interpreting negative contributions, for instance due to avoided processes and negative characterisation factors. For the key issue analysis, no such problems exist, because variances are always non-negative.

2.6.5 Results for ecoinvent'96

Table 7 shows a key issue analysis for the uncertainty in the atmospheric carbon dioxide emission associated with 1 TJ UCPTE-electricity. Three input uncertainties are responsible for 69% of the total uncertainty in CO_2. Of these three, two relate to the same process. Hence, one may reduce the uncertainty of the total CO_2 emission a factor of 2 by a more careful specification of only one process.

2.6.6 Performance

The time needed for carrying out a key issue analysis is only slightly larger than that for carrying out an analytical uncertainty analysis. Once an uncertainty analysis has been computed, CMLCA produces results for a key issue analysis within a few seconds. When no uncertainty analysis was carried out prior to the key issue analysis, the computation of the ecoinvent case is completed within a few minutes.

Table 7: Key issue analysis for carbon dioxide (to air) ([E25 in CMLCA) associated with the functional unit of 1 TJ UCPTE electricity ([G181] Strom-Mix UCPTE). Contributions to uncertainty below 2% are not shown; this explains that the entries shown accumulate to 85% of the total uncertainty only

Flow	Processes	Variance (kg^2)	%
[G181] electricity (UCPTE mix)	[P293] electricity (UCPTE mix)	4.83E7	51
[G182] electricity (West Germany)	[P293] electricity (UCPTE mix)	8.74E6	9
[G182] electricity (West Germany)	[P294] electricity (West Germany mix)	8.78E6	9
[G173] electricity (Italy mix)	[P285] electricity (Italy mix)	2.04E6	2
[G173] electricity (Italy mix)	[P293] electricity (UCPTE mix)	2.04E6	2
[G236] electricity from lignite power plant (Germany)	[P294] electricity (West Germany mix)	2.08E6	2
[G626] lignite power plant (Germany)	[P522] lignite power plant (Germany)	2.08E6	2
[E25] carbon dioxide (to air)	[P522] lignite power plant (Germany)	2.06E6	2
[G236] electricity from lignite power plant (Germany)	[P589] electricity from lignite power plant (Germany)	2.13E6	2
[G626] electricity from coal power plant (Germany)	[P589] electricity from lignite power plant (Germany)	2.08E6	2
[G414] electricity from coal power plant (Germany)	[P597] electricity from coal power plant (Germany)	1.43E6	2

3 Conclusions

3.1 Conclusions on the ecoinvent'96 database

One could sometimes feel the fears that the intrinsic sensitivity of such a complex system as ecoinvent is such that it is not possible to obtain meaningful results in LCA. These fears, however, were never substantiated, and neither were they refuted, so that they remained more an urban legend than an established fact. Without pretending to have provided a definite analysis for the ecoinvent, it is now possible to draw a few better-founded conclusions.

A contribution analysis is straightforward to execute, and reveals the underlying dependencies in an understandable way. In the present case, CO_2-emissions from UCPTE electricity highly depend on German coal-powered electricity.

Somewhat related to the topic of perturbation analysis is the concept of the condition number (Heijungs & Suh 2002). It is an overall measure of the instability of the system. Its logarithm indicates the amount of significant digits that may get lost (Thisted 1988). The condition number of the ecoinvent data matrix is dramatically large: about 10^{14}. This means that 15 significant digits of input information may be lost in the process of matrix inversion. And as most data in the ecoinvent database cannot be expected to be stated in more than one or two digits, one could claim that results obtained with this database have no meaning whatsoever. We should, however, keep in mind that the condition number can be regarded as an extreme worst-case indicator (Heijungs & Suh 2002, p. 138, Heijungs 2002). A more refined perturbation analysis confirms this. For most environmental flows, all multipliers are well between –1 and 1. Nevertheless, there are some multipliers on the order of 100. This indicates that an uncertainty of 1% propagates as an uncertainty of 100%. In other words, a quite modest uncertainty of 1% makes the output of 100% uncertain. Note, however, that this applies to only very few environmental flows, at least in the case of UCPTE electricity that was considered, where, for instance, the CO_2-emission is reasonably certain.

When an uncertainty analysis is carried out with a data uncertainty of 5% for all coefficients in the system, the output uncertainties for most environmental flows are between 7 and 15%. Only for the flows with extremely high multipliers, we find uncertainties in output that well exceed 100%, and that may rise as high as several thousand percent. These extreme uncertainties are remarkable, but perhaps even more remarkable is the relatively low uncertainty of most environmental flows. The uncertainty of CO_2, for instance, is only 7%. This picture emerges both for the analytical approach (by error propagation formulas) and the sampling approach (by Monte Carlo analysis).

An even more optimistic result is obtained with the discernibility analysis. Even when individual confidence intervals of several product alternatives show a large degree of overlap, a simultaneous analysis shows that the alternatives may still be significantly different and hence discernible.

The key issue analysis provides an easy way to find those coefficients of which a reduction of uncertainty is most needed. Of course, its practicality must be investigated by experience in a setting that transcends the ambitions of the research reported here.

3.2 Conclusions on life cycle interpretation

A first conclusion is the overwhelming number of methods for life cycle interpretation. If the precise difference in meaning between a perturbation analysis and an uncertainty analysis is already difficult to comprehend, the addition of a key issue analysis and the distinction between an analytical and a sampling uncertainty analysis may probably stupefy some people that have had no specific training in mathematics or statistics. That is certainly a problem in communicating the results of a life cycle interpretation, but one should also acknowledge that many numerical approaches towards interpretation are for the exclusive use of the LCA-practitioner: it supports the process of reiteration with respect to data collection. In that respect, it is to be regretted that guidance documents that stress the importance of iterative LCA setups do not mention practically available tools like the perturbation analysis. Several methods, most notably perturbation analysis and key issue analysis, will probably not be used for direct communication with the commissioner or the intended audience. Contribution analysis and comparative analysis may be used in that way, while uncertainty analysis and discernibility analysis may be presented in a slightly more friendly form.

Table 8: Overview of the suggested use of the different approaches towards life cycle interpretation under different conditions of availability of uncertainty information and for different purposes

Purpose of analysis	Uncertainty information available (or assumed)		
	None	Only standard deviation	Standard deviation and distribution
Focus in data collection	1. Contribution analysis 2. Perturbation analysis	Key issue analysis	–
Decision-support	Comparative analysis	Uncertain analysis (analytical)	1. Uncertain analysis (sampling) 2. Discernibility analysis

The practical application of numerical approaches to life cycle interpretation may be enhanced by the development of protocols for the successive use of these approaches in a context of iterative LCA-practice or decision-making. Perturbation analyses and key issue analyses may directly steer the data collection efforts, as it points out which data items should be collected with the highest precision and for which data items crude estimations may well be sufficient. On the other hand, comparative analyses combined with uncertainty analyses and discernibility analyses may provide information to a decision-maker, as these methods provide information on the ranking of alternative options and the robustness of this ranking under uncertainties in data. **Table 8** provides guidance in the use of the different approaches in various situations.

To many practitioners, sampling methods are more appealing than analytical approaches. But they have a clear disadvantage with respect to computation time. When one Monte Carlo run takes 30 seconds, 1000 runs require a working day. The analytical approach can reduce this to a few minutes, while the results are basically the same. Moreover, we see that a number of 100 Monte Carlo runs is sufficient for most parameters. Clearly, the message of Sonneman et al. (2003), that 'a full quantitative uncertainty assessment is, so far, too time consuming to be applied on each LCI as a default', needs some adjustment, given the availability of analytical methods and combined with the fact that these methods have a lower data demand (only the standard deviation suffices).

More generally, we see that there is a choice between analytical and sampling methods for an ordinary uncertainty analysis, while the key issue analysis is entirely based on an analytical method and the discernibilty analysis on a sampling method.

3.3 General conclusion

Although this paper reports only a few of the analyses that can be carried out, it clearly shows that numerical approaches to life cycle assessment can well be applied to a large system of interconnected processes, and that the analysis of the ecoinvent database reveals some of the subtleties of this system. In our view, life cycle interpretation should become a standard practice of any LCA that pretends to be more than a screening LCA. Sophisticated use of approaches that reside within the domain of interpretation should give us an understanding of the quality and robustness of the decision-support that is obtained with LCA. The knowledge on sensitivity and stability thus obtained should in its turn steer the collection of data with a sufficiently high quality. The perturbation analysis and the key issue analysis offer the possibility to discriminate between those data items for which a low or moderate data quality is sufficient, and those data items for which a high data quality is essential. Thus, sensitivity and robustness analyses facilitate an efficient data collection protocol. This once more stresses the iterative nature of the LCA process, where inventory analysis and interpretation are strongly interwoven.

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Appendix

This appendix lists our translations into English of the German names for processes, flows and compartments in ecoinvent'96 as far as they occur in this paper. Observe that no clear distinction between names of processes and their main outflow has been made in ecoinvent'96

Label	German name	English name
Processes		
[P218]	Wasser entkarbonisiert	decarbonized water
[P285]	Strom-Mix I	electricity (Italy mix)
[P293]	Strom-Mix UCPTE	electricity (UCPTE mix)
[P294]	Strom-Mix W-D	electricity (West Germany mix)
[P400]	Strom oelthermisch I	oil thermic electricity (Italy)
[P509]	Strom ab Brenngas-Kraftwerk I	electricity from gas power plant (Italy)
[P511]	Strom ab Brenngas-Kraftwerk NL	electricity from gas power plant (Netherlands)
[P513]	Strom ab Brenngas-Kraftwerk W-D	electricity from gas power plant (West Germany)
[P522]	Brk Kraftwerk in D	lignite power plant (Germany)
[P526]	Brk Kraftwerk in GR	lignite power plant (Greece)
[P580]	Stk Kraftwerk in D	coal power plant (Germany)
[P581]	Stk Kraftwerk in E	coal power plant (Spain)
[P583]	Stk Kraftwerk in F	coal power plant (France)
[P584]	Stk Kraftwerk in I	coal power plant (Italy)
[P585]	Stk Kraftwerk in NL	coal power plant (Netherlands)
[P589]	Strom ab Brk-Kraftwerk in D	electricity from lignite power plant (Germany)
[P597]	Strom ab Stk-Kraftwerk in D	electricity from coal power plant (Germany)
[P690]	Laufwasserkraft UCPTE	water flow power plant (UCPTE)
[P692]	Speicherkraft UCPTE	water barrage power plant (UCPTE)
[P922]	Rueckstaende Entkarbonisierung in Reststoffdeponie	residue decarbonization in storage
Economic flows		
Label	**German name**	**English name**
[G173]	Strom-Mix I	electricity (Italy mix)
[G181]	Strom-Mix UCPTE	electricity (UCPTE mix)
[G182]	Strom-Mix W-D	electricity (West Germany)
[G236]	Strom ab Brk-Kraftwerk in D	electricity from lignite power plant (Germany)
[G390]	Strom oelthermisch I	oil thermic electricity (Italy)
[W340]	Rueckstaende Entkarbonisierung in Reststoffdeponie	residue decarbonization in storage
[G414]	Strom ab Stk-Kraftwerk in D	electricity from coal power plant (Germany)
[G626]	Brk Kraftwerk in D	lignite power plant (Germany)
[G666]	Stk Kraftwerk in D	coal power plant (Germany)
[G753]	Laufwasserkraft UCPTE	water flow power plant (UCPTE)
[G755]	Speicherkraft UCPTE	water barrage power plant (UCPTE)
Environmental flows		
Label	**German name**	**English name**
[E20]	Cd Cadmium[Emissionen Luft]	cadmium (to air)
[E21]	CH_4 Methan[Emissionen Luft]	methane (to air)
[E22]	CN Cyanide[Emissionen Luft]	cyanide (to air)
[E23]	Co Cobalt[Emissionen Luft]	cobalt (to air)
[E24]	CO Kohlenmonoxid[Emissionen Luft]	carbon monoxide (to air)
[E25]	CO_2 Kohlendioxid[Emissionen Luft]	carbon dioxide (to air)
[E26]	Cr Chrom[Emissionen Luft]	chromium (to air)
[E27]	Cu Kupfer[Emissionen Luft]	copper (to air)
[E28]	Ethan[Emissionen Luft]	ethane (to air)
[E29]	Ethen[Emissionen Luft]	ethylene (to air)
[E30]	Ethin[Emissionen Luft]	acetylene (to air)
[E31]	Fe Eisen[Emissionen Luft]	iron (to air)
[E32]	H_2S Schwefelwasserstoff[Emissionen Luft]	hydrogen sulfide (to air)
[E33]	Hg Quecksilber[Emissionen Luft]	mercury (to air)
[E134]	R134a FKW[Emissionen Luft]	HFC-134a (to air)
[E135]	R22 FCKW[Emissionen Luft]	HCFC-22 (to air)
[E136]	Styrol[Emissionen Luft]	styrene (to air)
[E137]	TCDD-Aequivalente[Emissionen Luft]	dioxin/TEQ (to air)
[E138]	Tetrachlormethan[Emissionen Luft]	carbon tetrachloride (to air)
[E139]	Trichlormethan (Chloroform)[Emissionen Luft]	chloroform (to air)
[E140]	Vinyl Chlorid[Emissionen Luft]	vinyl chloride (to air)
[E141]	Xylole[Emissionen Luft]	xylene (to air)
[E142]	Abwaerme in Wasser[Emissionen Wasser]	waste heat (to water)
[E143]	Acenaphthene[Emissionen Wasser]	acenaphthene (to water)
[E144]	Acenaphthylene[Emissionen Wasser]	acenaphthylene (to water)
[E145]	Acrilonitrile[Emissionen Wasser]	acrilonitrile (to water)
[E146]	bis(2-ethylhexyl) Phtalat[Emissionen Wasser]	bis(2-ethylhexyl) phthalate (to water)
[E147]	BSB5[Emissionen Wasser]	BOD5 (to water)
[E148]	Butyl Benzyl Phtalat[Emissionen Wasser]	butyl benzyl phthalate (to water)
[E149]	Chlor. 1,1,1-Trichlorethan[Emissionen Wasser]	1,1,1-trichlorethane (to water)
[E455]	Schwebestoffe[Emissionen Wasser]	suspended particles (to water)
Compartments		
Label	**German name**	**English name**
[M4]	Emissionen Luft	emissions to air
[M5]	Emissionen Wasser	emissions to water