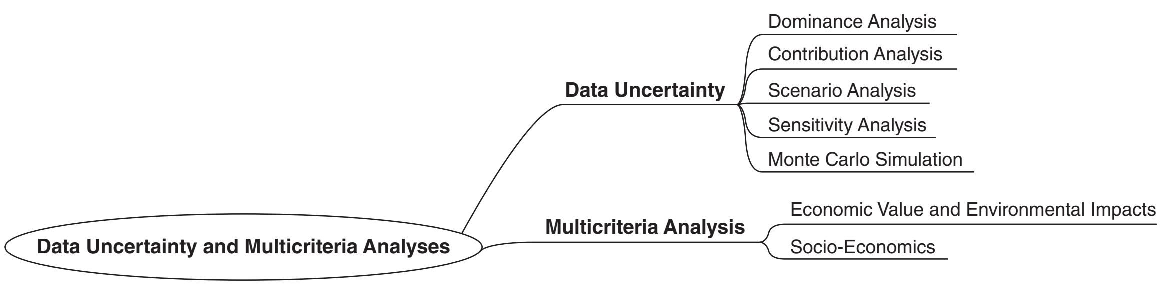
5

Data Uncertainty and Multicriteria Analyses



Structure for Lecture Planning

5.1 Data Uncertainty Analysis

LCA (Chapter 4) results have a number of data uncertainties. A transparent approach aims to track the uncertainties in data and reduce the effects of uncertainties in data. Data uncertainty in LCA can result from imprecise measurements of inventories, average or even outdated data using proxies and incomplete data. Various assumptions are made when deducing life cycle inventories (LCI), such as linear correlations and averaged data over time and across regions. During life cycle impact assessments (LCIAs), model approximations can result from average characterization factors deduced from simple biogeochemical models. Missing characterization factors for certain substances and interactions between substances are also approximated. Data uncertainties result from normalization, weighting and valuation stages.

Uncertainties can result due to choices of:

1. Functional units, systems boundaries.
2. LCI.
3. LCIA.
4. Allocation approaches for multioutput and for recycling processes.

Biorefineries and Chemical Processes: Design, Integration and Sustainability Analysis, First Edition.
Jhuma Sadhukhan, Kok Siew Ng and Elias Martinez Hernandez.

Companion Website: http://www.wiley.com/go/sadhukhan/biorefineries

When all errors are accumulated for data interpretation, the errors can be large. Most LCA results present spatially and temporally averaged data and in this approach resulting errors are also difficult to comprehend. Data uncertainty can be managed by probabilistic or stochastic approaches such as Monte Carlo simulation, and also some deterministic ways such as scenario analysis and sensitivity analysis.

The LCA results include the following aspects:

1. Dominance analysis
2. Contribution analysis
3. Testing robustness of the results
   - Scenario analysis
   - Sensitivity analysis
   - Monte Carlo simulations

5.1.1 Dominance Analysis

A dominance analysis is about hot spot analysis due to environmental activities. The analysis shows what activity has the highest value in an impact category. Dominance analysis results can be shown in various ways. The pie charts in Figure 5.1 show examples of the sequence of activities from the most to the least detrimental activities for the environment. Cumulative primary energy depletion and global warming, acidification and abiotic depletion potential categories are shown[1]. The agricultural system shown is for UK wheat, comprising the FO: Field Operations, F & P: Fertilizers and Pesticides, Dir. & Ind. FE: Direct and Indirect Field Emissions, GC: Grain Conditioning.

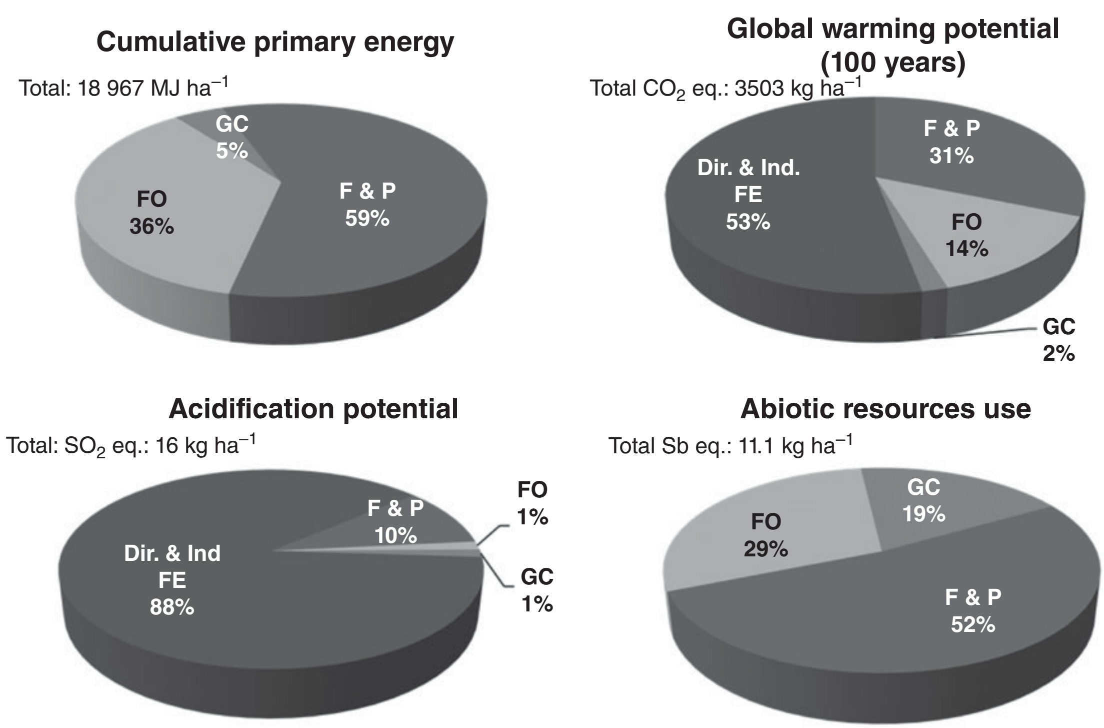


Figure 5.1 An example of dominance analysis results. (Reproduced with permission from Martinez-Hernandez et al. (2013)[1]. Copyright © 2013, Elsevier.)

The activities, from the highest to the lowest impacts are as follows:

Cumulative primary energy:

$$F \ \& \ P > FO > GC$$

Global warming potential:

$$\text{Dir. \& Ind. FE} > F \ \& \ P > FO > GC$$

Acidification potential:

$$\text{Dir. \& Ind. FE} > F \ \& \ P > FO/GC$$

Abiotic resource use:

$$F \ \& \ P > FO > GC$$

Note that the total values of the impact characterizations are shown on a per hectare basis. This is a transferable form to compare with other equivalent systems, such as first generation crops.

A Sankey diagram is another way to present the hot spot analysis from various activities. In a Sankey diagram, the thickness of a link joining a source to a sink process is proportional to the environmental impact from the source process. A much thicker line from a source process than a line entering to the process shows that the process is environmentally more detrimental. The line thickness increases from upstream to downstream processes as environmental impacts are aggregated. The life cycle global warming potential (GWP) (as CO_2 equivalent) in g MJ^{-1} of two integrated whole *Jatropha* fruit biorefinery systems producing heat and power and (a) biodiesel or (b) green diesel is shown in Figure 5.2. The combustion processes have the highest GWP impacts, followed by the integrated biomass gasification combined cycle (IBGCC) plants producing methanol or hydrogen.

5.1.2 Contribution Analysis

Chemicals causing higher environmental impacts must be identified and replaced with environmentally better performing similar functionality chemicals. This is also a hot spot analysis, but one related to chemicals or loads or polluting substances rather than activities as in the case of dominance analysis. Thus contribution analysis is carried out to track back pollutants to their origins and minimize their emissions from the origin.

Figure 5.3 shows an example of a contribution analysis. The outlet pollutants include carbon dioxide, nitrous oxide and methane in kg per tonne of sewage sludge. These flow rates do not account for the GWP impact characterization factors, such as 298 CO_2 equivalent for nitrous oxide and 25 CO_2 equivalent for methane. You are recommended to use CO_2 equivalent values on the y-axis for direct comparisons, through a contribution analysis. Note that the outlet carbon dioxide quantities do not take account of the inlet carbon dioxide capture during biomass production.

Figure 5.4 shows the contribution analysis of nonrenewable and renewable energy resources for the production of biogas for micro generation (electricity and heat generations) and digested matter for agricultural application (fertilizer production) from sewage sludge anaerobic digestion (AD). Tracking back the GHG emissions, the primary energy resources such as natural gas (by 61%), crude oil (by 5%) and hard coal and lignite (each by 2%), out of a total of 2468.5 MJ of energy input, were found to be responsible. The functional unit is 1000 kg of sewage sludge AD into 315 N m^3 of biogas and 700 kg of digested matter productions. If natural gas is replaced with a renewable energy source, the GHG emissions will be reduced. Note that the organic substance, primary forest and wind and solar energy use is close to zero. Hence, increasing their inputs to the AD system, in particular solar and wind energy, will reduce the environmental emissions. Tracking the routes between primary resources and end uses through conversion processes is essential. The pollutants causing impact hot spots, pollutants with larger impact reduction potentials and the primary resources of pollutants need to be identified. Primary resources causing depletion of energy or material reserves of the earth and emissions can be replaced with better alternatives that reduce these environmental impacts.

A contribution analysis is very useful for identifying resource (elements and fossil) use. The input resources required for the production of polyethylene terephthalate for 1 cm^2 solar organic photovoltaic (OPV) cell fabrication, extracted from Ecoinvent 2.0 and BUWAL databases, are shown in Table 5.1.

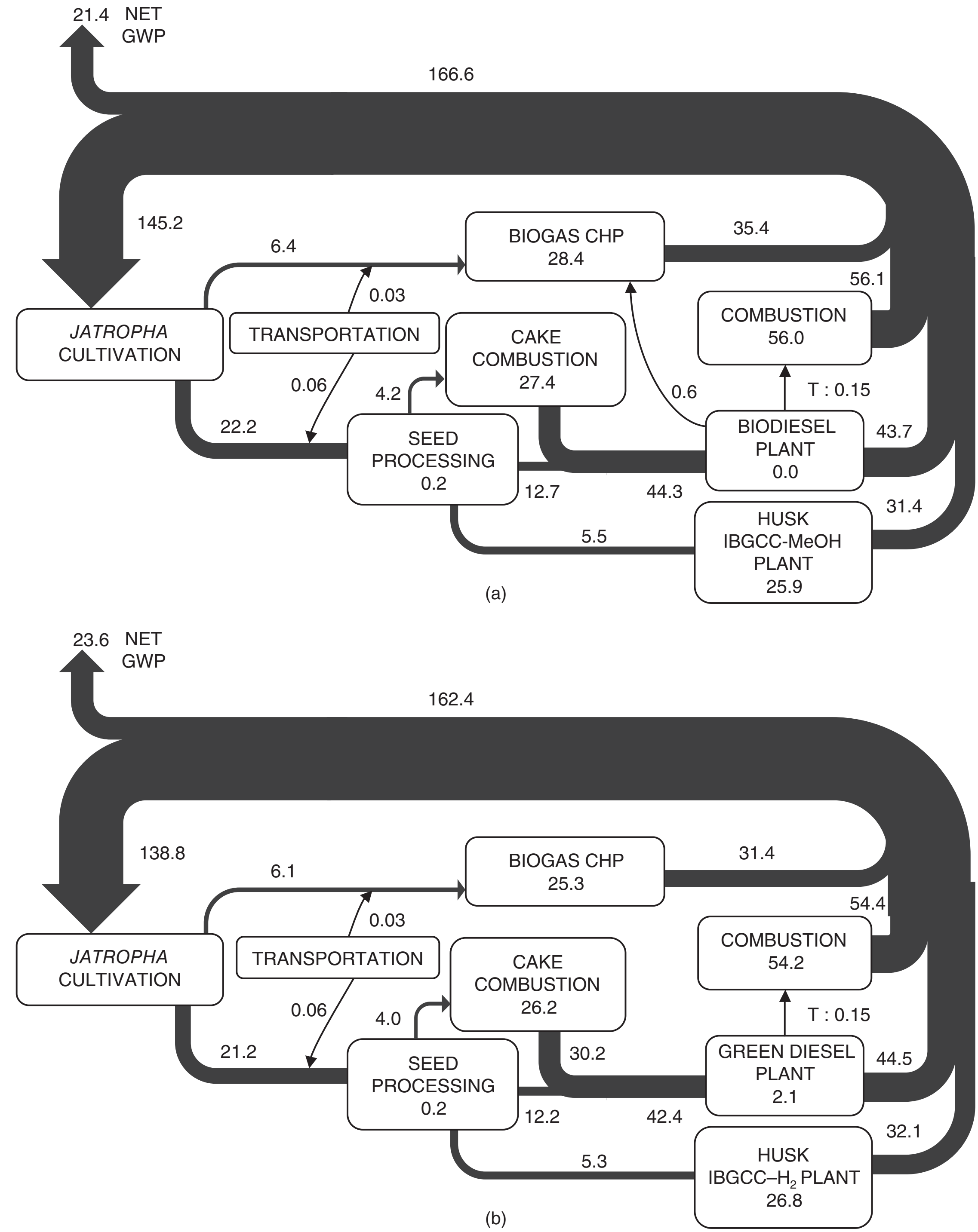


Figure 5.2 *Sankey diagram for GWP (as CO_2 equivalent) flows in g MJ^{-1} in two integrated whole* Jatropha *fruit biorefinery systems producing heat and power and (a) biodiesel or (b) green diesel.*

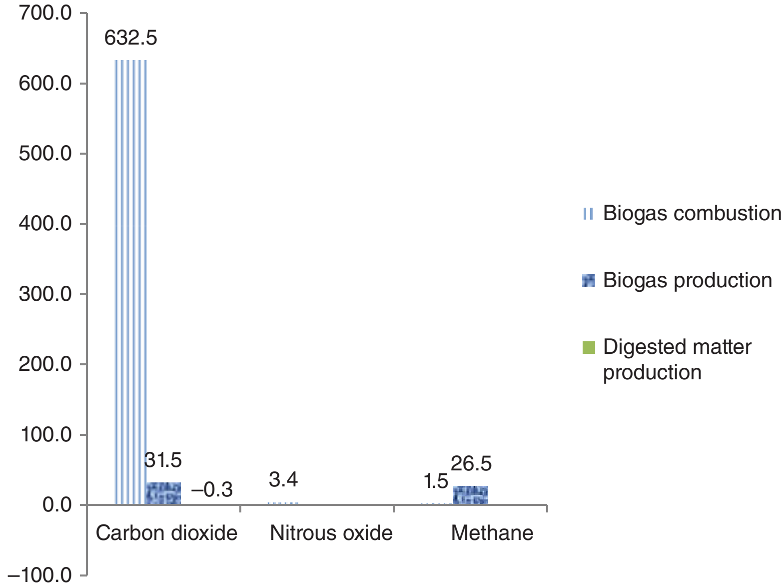


Figure 5.3 Contribution analysis in kg per tonne of sewage sludge (which environmental load contributes the most).

5.1.3 Scenario Analysis

At first, independent variables are fixed at certain values for an LCIA. Independent variables can be varied to generate numerous scenarios. One or more independent variables can be varied at the same time. A sensitivity analysis refers to variations in estimated impact potentials due to unit changes in independent variables or due to standard deviations from mean values of independent variables. Independent variables, one or more at a time, can be examined for a sensitivity

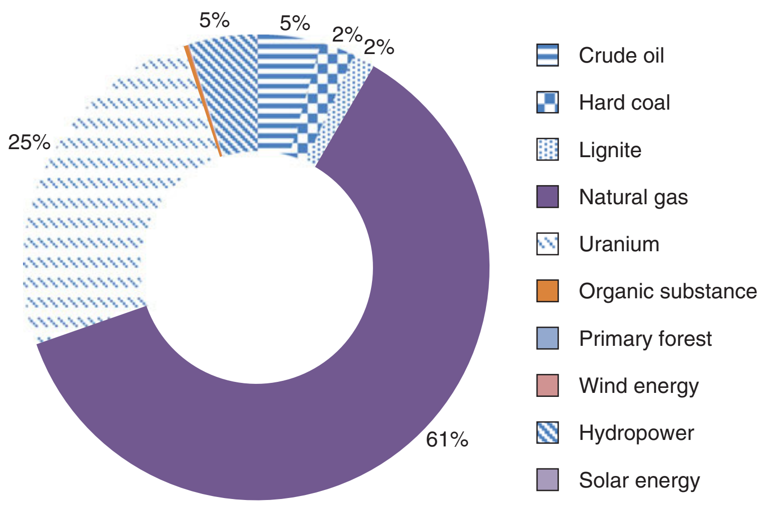


Figure 5.4 Contribution analysis of nonrenewable and renewable energy resource use for the production of biogas for micro generation (electricity and heat generations) and digested matter for agricultural application.

Table 5.1 *Resource depletion from the manufacture of a solar OPV cell. Some databases were obtained from BUWAL (Bundesamt für Umwelt, Wald und Landschaft).*

Crude oil free wellhead [crude oil (resource)]	1.07 kg
Raw natural gas (BUWAL) [natural gas (resource)]	0.576 kg
Primary energy from hydropower (BUWAL) (renewable energy resources)	0.5 MJ
Raw hard coal (BUWAL) [hard coal (resource)]	0.13 kg
Raw brown coal (BUWAL) [lignite (resource)]	0.11 kg
Process and cooling water [operating materials]	0.017 kg
Sodium chloride (rock salt) [nonrenewable resources]	0.0049 kg
Iron ore [nonrenewable resources]	0.0005 kg
Bauxite [nonrenewable resources]	0.0003 kg
Limestone (calcium carbonate) [nonrenewable resources]	0.00025 kg
Quartz sand (silica sand; silicon dioxide) [nonrenewable resources]	2.00×10^{-5} kg
Uranium free ore (BUWAL) [uranium (resource)]	1.60×10^{-6} kg

analysis on the environmental impacts. More sensitive independent variables displaying greater chances of variations from their mean values can be selected for further analyses. A number of scenarios can be evaluated using extreme bounds of independent variables and combinations of their values within feasible ranges.

An example of 1 tonne of epoxy resin production from biomass is shown in Table 5.2. Hexane and nitrogen mass flow rates are the two key input independent variables to the LCIA model. Their values are varied within feasible ranges to examine their combined effects on the GWP estimates from the LCIA model. The base value of GWP is 518.46 kg CO_2 equivalent from 1 tonne of epoxy resin production; 3 kg of hexane and 13 kg of nitrogen mass inputs to the system, for example, achieve a GWP reduction by 25%. As can be seen, the hexane mass flow rate can be varied between 3 kg and 99 kg and the nitrogen mass flow rate between 5 kg and 15 kg. For various combinations of their input values within these ranges, impact potentials can be evaluated. This method is called a scenario analysis. Two extreme scenarios can be created: maximum GWP reduction by 25% and minimum GWP reduction by 8% from the base impact value. A number of other scenarios result in 19% and 14% reductions in GWP. One or both flow rates can be varied at the same time.

Table 5.2 *Hexane and nitrogen mass flow rates for various reductions from the base value of GWP impact.*

Hexane Mass Flow Rate (kg)	Nitrogen Mass Flow Rate (kg)	GWP (100 years) Reduction (%)
3	13	
12	12	
31	10	25
60	7	
78	5	
18	15	
27	14	
37	13	19
46	12	
65	10	
93	7	
46	15	
55	14	
65	13	14
74	12	
93	10	
89	14	8
99	13	

5.1.4 Sensitivity Analysis

To do a sensitivity analysis with respect to an independent parameter, a range is specified and variations in LCI and LCIA are estimated for the range. An example is shown in Figure 5.5. A sewage sludge AD system producing biogas for micro generation (electricity and heat generations) and digested matter for fertilizer production is studied for the sensitivity analysis. The independent variable is the biogas volumetric production rate. All other flow rates are dependent on the biogas volumetric production rate. These include digested matter mass flow rate, electricity and heat generation, etc. The biogas volumetric production rate is varied by ±25% standard deviation from the mean value and the LCIA are examined. The variations in the LCIA from their mean values are shown in Figure 5.5. The plot was generated using the graph:stock:high–low–close (this applies as maximum-minimum-mean) option in the Excel spreadsheet. Note that the values are not shown in absolute terms, but in relative terms. Thus, the base value is taken as 100; the mean value is marked at ~100. The minimum and maximum values are thus below and above 100, respectively. The difference between maximum and mean values is the positive standard deviation from the mean value. The difference between minimum and mean values is the negative standard deviation from the mean value. The difference between maximum and minimum values is defined as the range.

Impact categories include the acidification potential (AP) in kg SO_2 equivalent, eutrophication potential (EP) in kg phosphate equivalent, freshwater aquatic ecotoxicity potential (FAETP) in kg 1,4-dichlorobenzene (DCB) equivalent, global warming potential (GWP) in kg CO_2 equivalent, human toxicity potential (HTP) in kg DCB equivalent, marine aquatic ecotoxicity potential (MAETP) in kg DCB equivalent, photochemical oxidant creation potential (POCP) in kg ethylene equivalent and terrestric ecotoxicity potential (TETP) in kg DCB equivalent.

The maximum range is obtained for the POCP, 38.2%, from 80.92 to 119.12. Its standard deviation is thus ±19.1% from its mean value. The high–low–close stock graphical choice in the Excel spreadsheet was used to create this range: 119.12 (high)–80.92 (low)–100.02 (close). This graph shows the sensitive impact categories with greater ranges. Thus, POCP is the most sensitive and MAETP is the least sensitive impact category. MAETP is the least sensitive impact

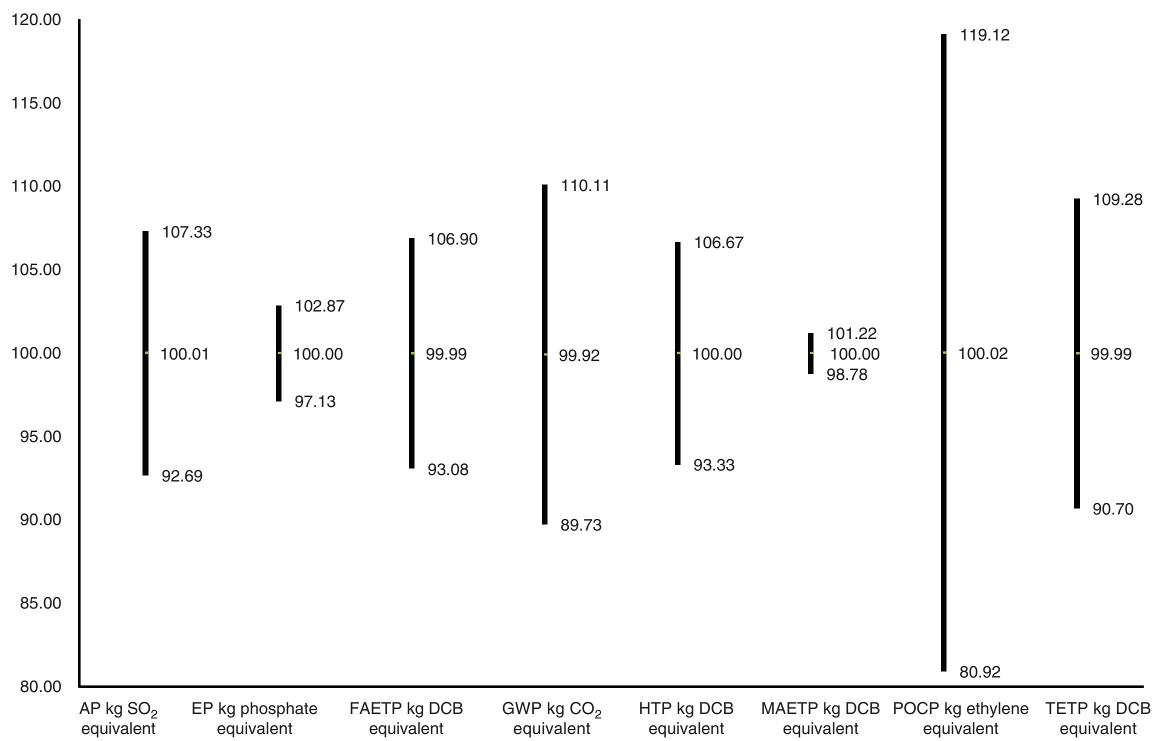


Figure 5.5 *Sewage sludge to micro generation and digested matter: range of variations from the mean values due to ±25% standard deviation in the independent variable (biogas volumetric production rate).*

category due to its very large value and narrow range. The most to the least sensitive life cycle impact categories are as follows:

POCP > GWP > TETP > AP > FAETP > EP > MAETP

5.1.5 Monte Carlo Simulation

Sensitivity analysis can be undertaken for a multiparametric decision making problem using a Monte Carlo simulation combined LCA (MCLCA) approach. With MCLCA important impact characterizations can be selected and optimized to make a choice between various technologies. In Monte Carlo simulation, values of independent variables within their specified standard deviations from their mean values can be randomly selected during a simulation run. All the primary impact characterizations are calculated for the selected set of values of independent variables. At the end of all Monte Carlo simulation runs, the chances or probabilities of occurrence at various values of an impact characterization are counted and plotted (on the y-axis) against percentage standard deviations from mean value of the impact characterization (on the x-axis). This results in the probability distribution curve of an impact category. Highly sensitive categories show wider probability distributions. Narrow probability distribution curves imply less sensitive categories.

Intergovernmental Panel on Climate Change (IPCC) Guidelines for National Greenhouse Gas Inventories; Geneva, Switzerland, 2006, recommended a Monte Carlo simulation to estimate and mitigate uncertainty in impact assessments[2]. The methodology can be adapted according to the LCA goal and scope definition. Figure 5.6 shows the steps involved in an uncertainty analysis using a Monte Carlo simulation. The MCLCA approach consists of three main steps:

1. Develop equations or models for the LCI in terms of independent and uncertain input variables to the model.
2. Select a standard deviation and probability distribution function for each independent variable.

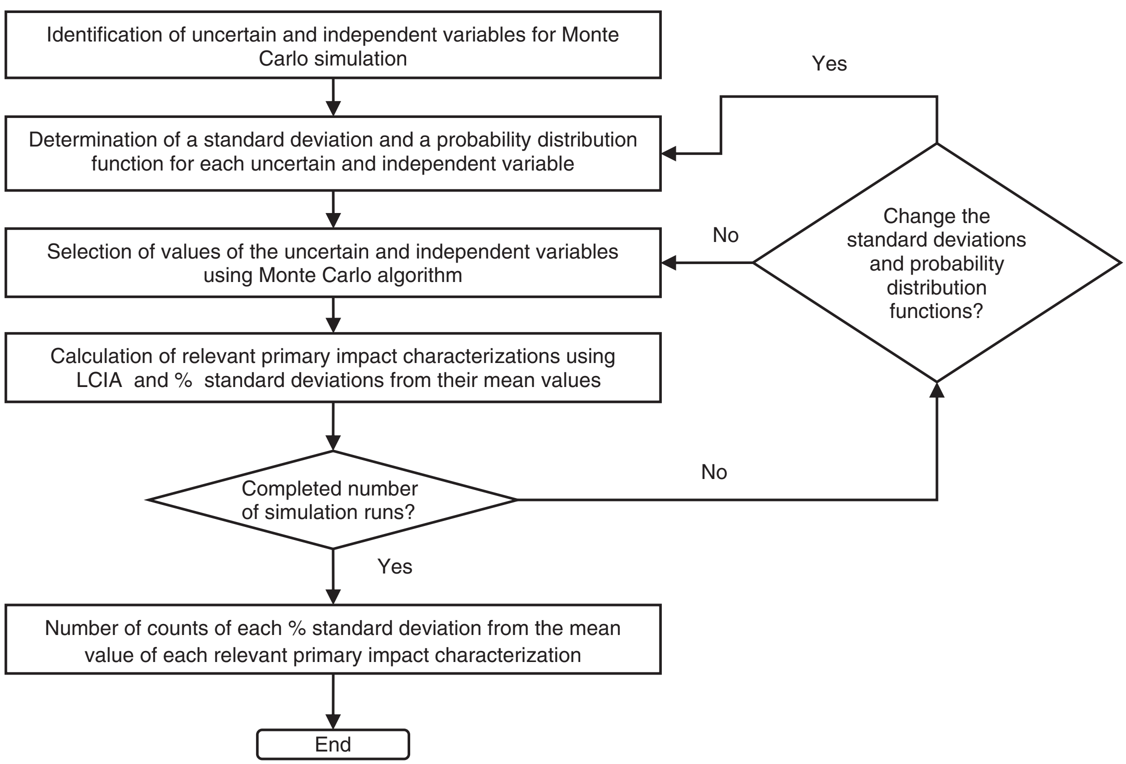


Figure 5.6 Monte Carlo simulation framework integrated with LCA.

3. Monte Carlo simulation run. Using the Monte Carlo algorithm (for random number generation), a set of values of independent variables within their given distributions is randomly selected. Determine the LCIA. At the end of a large number of specified simulation runs, count the occurrence of an impact characterization at the estimated values.
4. Repeat the Monte Carlo simulation runs, steps 2 to 3, until enough number of runs is completed for obtaining smooth distribution trends of the LCIA. Calculate the mean value and standard deviations from the mean value for each impact category.
5. Count the chances of occurrence of each model predicted impact characterization by the % standard deviation from their mean values. Ensure that there are enough simulation runs to obtain a smooth and representative probability distribution curve for an impact category.

LCA is data intensive. A dispersed data set makes MCLCA computationally intensive. There lies uncertainty in primary raw material and energy flow data assimilation and in an inventory analysis. A large number of Monte Carlo simulation runs ensures that the approximation can be made more accurately. Monte Carlo simulation runs of ~5000 are recommended in the IPCC Guidelines[2].

The equation below shows the formula for calculating the standard deviation, σ, of n data points: $x_1, x_2, x_3, \ldots, x_{n-1}, x_n$, with respect to their average or mean value, $\bar{x}$:

$$\sigma = \sqrt{\frac{\sum_i (x_i - \bar{x})^2}{n}} \tag{5.1}$$

The values of independent variables are generated using their given probability distribution functions. The simplest form of probability distribution function is the uniform probability distribution function. Three other most common forms of probability distribution functions are the normal or Gaussian, lognormal and triangular.

Equations (5.2a) to (5.2c) below show their respective correlations in terms of mean, standard deviation and values of the variable (x_i):

Normal or Gaussian probability distribution function =

$$f(x_i) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_i - \bar{x})^2}{2\sigma^2}\right)^{\pi} \tag{5.2a}$$

Lognormal probability distribution function =

$$f(x_i) = \frac{1}{x_i\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(\ln x_i - \bar{x})^2}{2\sigma^2}\right)^{\pi} \tag{5.2b}$$

Triangular probability distribution function =

$$f(x_i) = \left\{\begin{array}{c} 0(x_i \le a; x_i \ge c) \\ \dfrac{2(x_i - a)}{(b-a)(c-a)}(a < x_i < b) \\ \dfrac{2(c - x_i)}{(c-a)(c-b)}(b \le x_i < c) \end{array}\right\} \tag{5.2c}$$

where

a = minimum value of x
b = modal value of x
c = maximum value of x

A sewage sludge AD plant can be operated to maximize the output energy generation via biogas production. An AD plant also coproduces digested matter for agricultural application. The biogas and digested matter yields are related by the mass balance for a given sewage sludge mass throughput through an AD plant. As the biogas yield increases, the energy generation increases and digested matter yield decreases, lowering the fertilizer production rate and vice versa. Hence, one

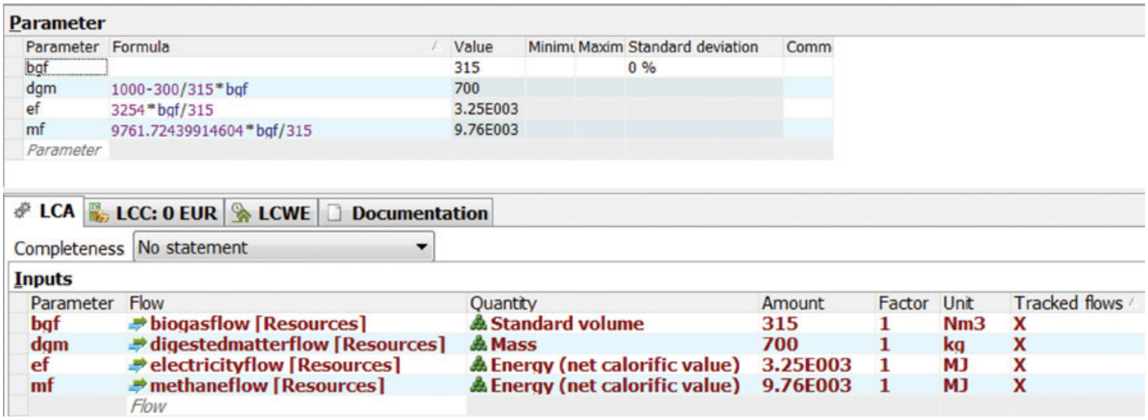


Figure 5.7 *Screenshot from GaBi, to define the independent and dependent parameters involved in an AD plant LCA study.*

of the mass yields of biogas and digested matter can be considered as an independent variable and the other can be shown as a function of the independent variable. The following example and data analysis show a systematic decision making about the transfer coefficient of sewage sludge for energy generation an against agricultural application. The problem can be formulated for sensitivity analysis, Monte Carlo simulations, etc., and solved in a spreadsheet environment or any other software supporting such analyses.

Figure 5.7 shows a screenshot from GaBi, LCA software from PE International, to define the independent and dependent variables of an AD plant. Independent variables do not have any formula, while the dependent variables are formulated in terms of independent variables. In the figure, the biogas volumetric flow rate, presented by the symbol `bgf`, is shown as the independent variable carrying no formula in the formula bar. The dependent variables: digested matter mass flow rate, electricity generation and methane calorific value, using the symbols `dgm`, `ef` and `mf`, respectively, are shown as a function of `bgf`. The correlations are linear with respect to `bgf`. A Monte Carlo simulation is then undertaken with:

(a) 5000 runs,
(b) ±25% standard deviations and normal distributions in `bgf`.

The probability distribution of the global warming potential impact with respect to its mean value in ±100% standard deviation scale is shown in Figure 5.8. For example, the probability of the global warming potential occurring at the

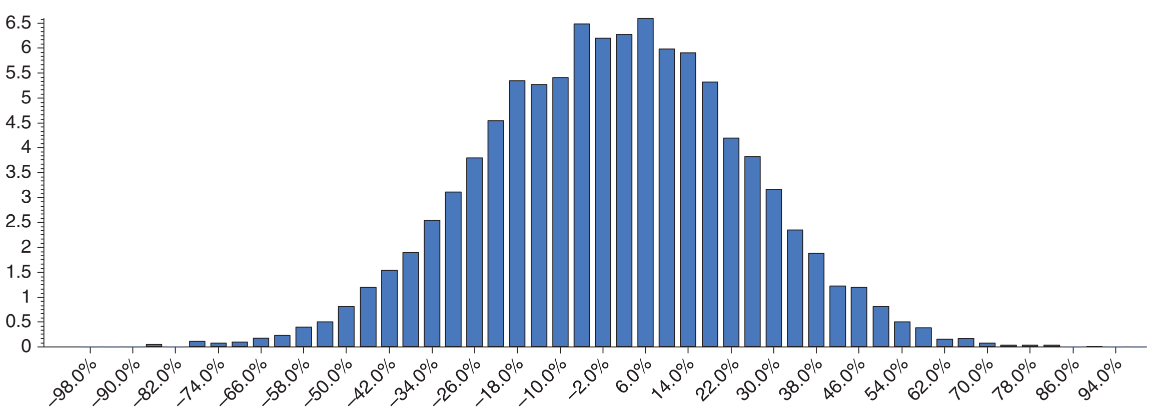


Figure 5.8 *Probability distribution of the global warming potential impact in ±100% standard deviation scale from the mean.*

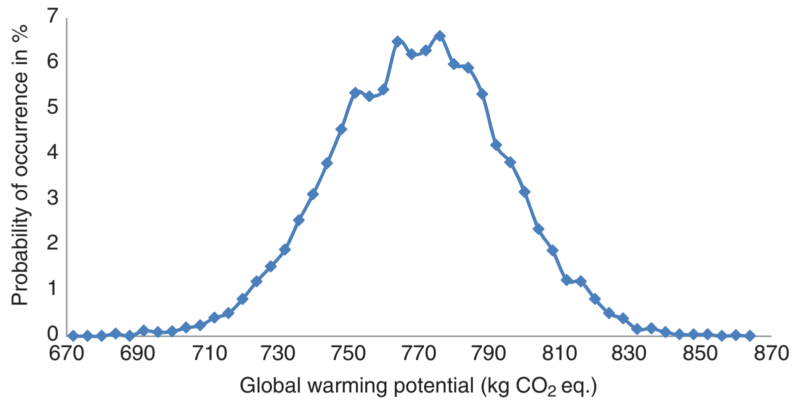


Figure 5.9 *Probability distribution against the global warming potential impact values.*

mean value is ~6.3%. The peak probability, ~6.6%, occurs at the standard deviation of ±6%. The summation of all the probabilities across the ±100% standard deviation scale is 100. The resulting distribution corresponds to the normal distribution.

It is also possible to generate the data points or actual impact values from a probability distribution curve in Figure 5.8, using Equation (5.1). The probability distribution against the actual impact values can then be plotted, such as in Figure 5.9. The mean global warming potential is 768 kg CO_2 equivalent. The number of data points or clusters is 49.

The probability distributions of FAETP, HTP and TETP with respect to standard deviations are shown in Figure 5.10. As TETP displays a wider distribution it has a greater chance of change from the mean value. Figure 5.11 similarly shows that the probability of occurrence of MAETP at the mean value is 98% and hence the probability of reduction (or increase) in the MAETP mean value is only 2%. This is due to the MAETP's very high absolute mean value in the order of 10^4 magnitudes in kg DCB equivalent. EP also shows a narrow distribution, but it is wider than that of MAETP. This analysis thereby helps to screen out the most sensitive set of impact categories for further investigation. For the given example, the GWP showing wider distribution is the most sensitive impact category. The MAETP showing the narrowest

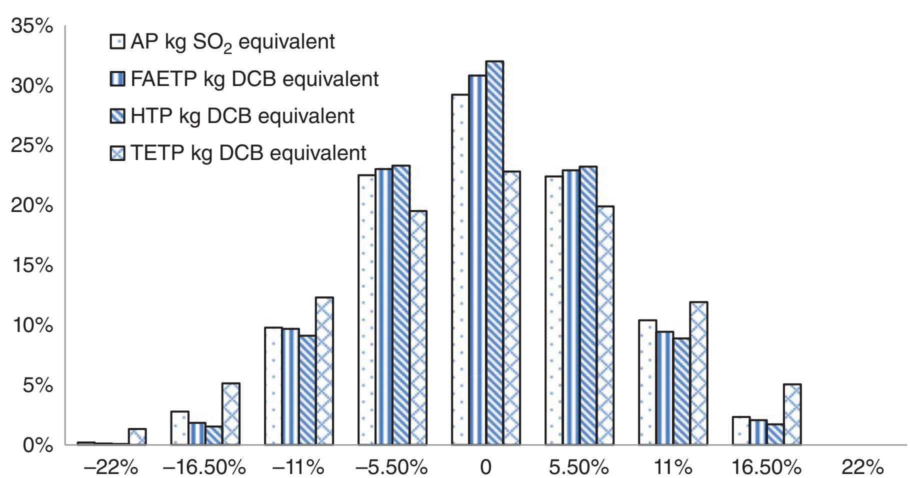


Figure 5.10 *Acidification, freshwater aquatic ecotoxicity, human toxicity and terrestric ecotoxicity potentials (AP, FAETP, HTP and TETP) impact probability distributions (y axis) with respect to standard deviations (x axis) from their mean values.*

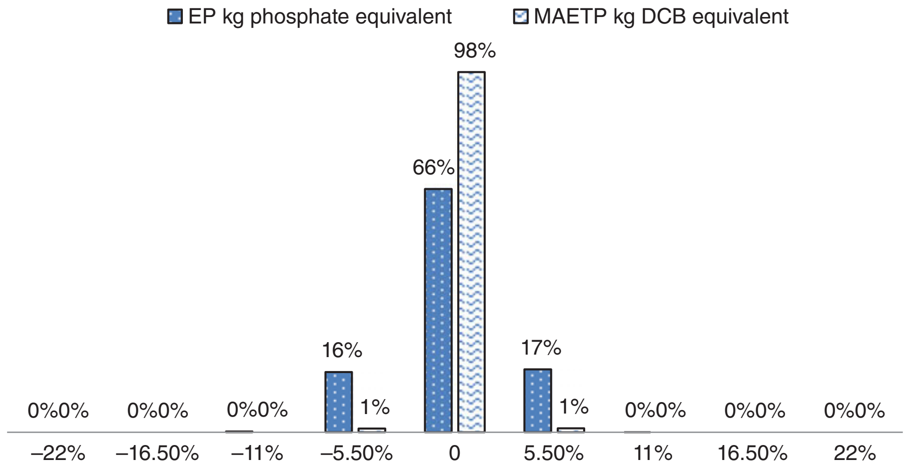


Figure 5.11 *Probability distributions (y axis) of marine aquatic ecotoxicity potential (MAETP) and eutrophication potential (EP) with respect to standard deviations (x axis) from their mean values.*

distribution is the least sensitive impact category. The least sensitive categories also imply that they will not be affected by model uncertainties.

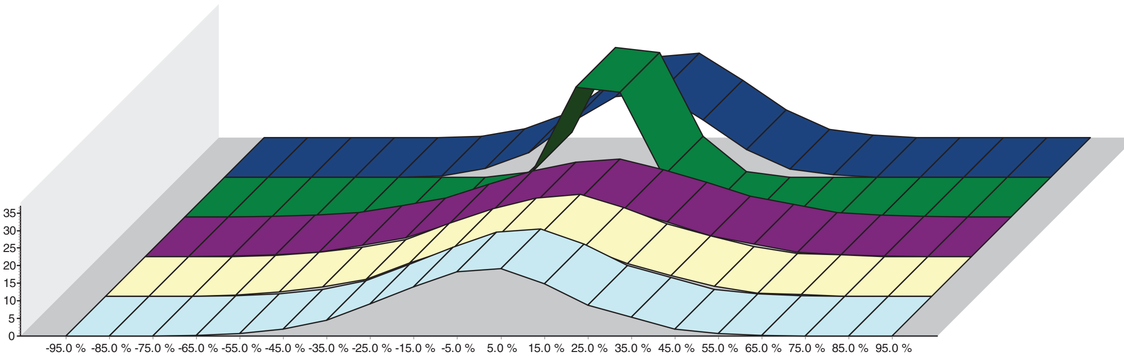
Figure 5.12 shows the probability distribution versus the standard deviation from the mean value of various impact categories using GaBi software.

The recommended specifications for the Monte Carlo simulation are:

(a) 5000 runs
(b) Normal distributions and standard deviations by ±25% of independent variables
(c) Capture ±100% standard deviations scale for the impact characterizations.

Ouantitv/Weighting	Unit/Normalization	Special	View	Basis scenario	Mean value	Standard deviation	10% Percentile	25% Percentile	Median	75% Percentile	90% Percentile	-100.0%	-90.0%	-80.0%
CML2001 - Nov. 2010. Acidification Potential (AP)	ka SO2-Equiv.	Total	1	**0.414**	**0.416**	**15.9 %**	0.332	0.371	0.416	0.46	0.501	0 %	0 %	0 %
CML2001 - Nov. 2010. Eutrophication Potential (EP)	ka Phosphate-Equiv.	Total	2	**2.59**	**2.59**	**9.27 %**	2.28	2.42	2.59	2.75	2.89	0 %	0 %	0 %
CML2001 - Nov. 2010. Global Warming Potential (GWP 100 vears)	ka CO2-Equiv.	Total	3	**774**	**778**	**24.6 %**	535	650	779	907	1.03E003	0.02 %	0.06 %	0.18 %
CML2001 - Nov. 2010. Ozone Laver Depletion Potential (ODP. steadv state)	ka R11-Equiv.	Total	4	**1.46E-005**	**1.47E-005**	**23. %**	1.04E-005	1.24E-005	1.47E-005	1.7E-005	1.91E-005	0 %	0.06 %	0.04 %
CML2001 - Nov. 2010. Photochem. Ozone Creation Potential (POCP)	ka Ethene-Equiv.	Total	5	**0.0533**	**0.0535**	**21.1 %**	0.0391	0.0459	0.0535	0.0611	0.0681	0 %	0.02 %	0.06 %

Figure 5.12 *Probability distribution versus standard deviation from the mean value of various impact categories using GaBi software.*



Quantity/Weighting	Unit/Normalization	Special	View	Basis scenario	Mean value	Standard deviation
CML2001 - Nov. 2010, Acidification Potential (AP)	kg SO2-Equiv.	Total	1	**0.414**	**0.416**	**15.9 %**
CML2001 - Nov. 2010, Eutrophication Potential (EP)	kg Phosphate-Equiv.	Total	2	**2.59**	**2.59**	**9.27 %**
CML2001 - Nov. 2010, Global Warming Potential (GWP 100 years)	kg CO2-Equiv.	Total	3	**774**	**778**	**24.6 %**
CML2001 - Nov. 2010, Ozone Layer Depletion Potential (ODP, steady state)	kg R11-Equiv.	Total	4	**1.46E-005**	**1.47E-005**	**23 %**
CML2001 - Nov. 2010, Photochem. Ozone Creation Potential (POCP)	kg Ethene-Equiv.	Total	5	**0.0533**	**0.0535**	**21.1 %**

Figure 5.13 *3D plots of probability distributions of impact characterizations given in Figure 5.12.*

Figure 5.13 shows the 3D plots of probability distributions of impact characterizations given in Figure 5.12.

The following list is the summary of MCLCA approach:

- Standard deviations from mean values and nature of distributions are specified for independent variables.
- Values of independent variables can be randomly selected within the given specifications during a simulation run.
- All the primary impact characterizations are calculated for the randomly selected set of values of independent variables.
- Another set of values of independent variables are randomly selected within their specified ranges. This is called a Monte Carlo simulation run. Several runs (~5000) are repeated.
- The total number of runs is specified and the above steps are repeated until all the runs are completed.
- At the end of all Monte Carlo simulation runs, the probability distribution of each impact characterization for various percentage standard deviations from the mean value is counted. The impact characterizations that can be reduced by adjusting values of independent variables show a wider probability distribution and vice versa.

5.2 Multicriteria Analysis

Sustainable development calls for a multicriteria analysis, including social, economic and environmental impact assessments. While LCA is a tool for environmental sustainability analysis, social and economic impacts can also be assessed over life cycles. These are called social LCA (SLCA) and life cycle cost (LCC), respectively. Similar to LCA, SLCA and LCC show corresponding hot spots and ways of mitigation. The hot spots can span across the time scale (life cycle) as well as geographic regions (supply chains). The SLCA and LCC can be applied in the same way as LCA, for accounting (consequential) and change oriented (attributional) systems, discussed in Chapter 4.

Figure 5.14 shows the desirable domain for multicriteria analysis combining LCA, SLCA and LCC tools. Table 5.3 shows the various SLCA categories. The analysis proceeds in the same way, from primary through mid-point to end-point impacts. The analysis is to help decision making about sustainable supply chains by eliminating hot spots and mitigating potential negative or rebound impacts.

SLCA, an evolving tool, is discussed in 2009 UNEP/SETAC *Guidelines for Social Life Cycle Assessment* for SLCA; http://socialhotspot.org/user-portal-2/portal-info also "offers an online database that allows users to browse data on social risks by sector, country, or risk theme. There are choices of 227 countries and 57 economic sectors. The data

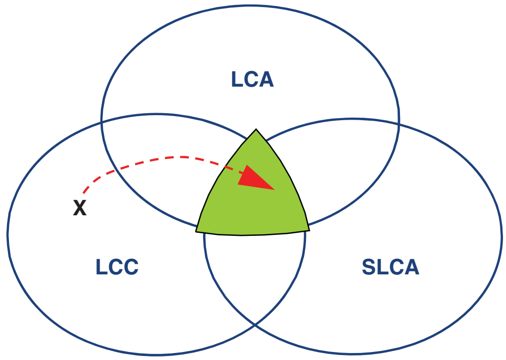


Figure 5.14 *Multicriteria analysis combining LCA, SLCA and LCC tools.*

comprehensively addresses social issues on human rights, working conditions, community impacts and governance issues, via a set of nearly 150 risk indicators grouped within 22 themes. Risks are also expressed, whenever relevant, by country and sector." LCC is implemented using a net present value and discounted cash flow analysis; this is discussed in Chapters 2, 6 and 7.

5.2.1 Economic Value and Environmental Impact Analysis of Biorefinery Systems

The biorefinery system shown in Figure 5.15 has biomass production, product manufacturing, end use and construction materials' life cycle process blocks. The two commonly used system boundaries include cradle to grave and cradle to gate with and without the carbon dioxide sequestration or capture by biomass and biorefinery products' end use blocks, respectively. Each block causes primary resource depletion (input) and emission impacts (output) that are accounted for in the LCA.

The contribution analysis of a biorefinery system shows typical characteristics in the environmental impact against an added cost profile. Raw materials, energy, raw materials for plant installations (capital good raw materials) and emissions are the four main loads interacting between biorefinery systems and the environment. Their environmental impacts decrease in the following sequence:

Emissions > Raw materials > Energy (provided that the energy required by the biorefinery systems can be supplied from renewable sources) > Capital good raw materials

Table 5.3 *SLCA categories.*

Labor Rights	Health and Safety	Human Rights	Governance	Community Infrastructure
1. Child labor	1. Injuries	1. Indigenous rights	1. Legal systems	1. Medical facilities
2. Forced labor	2. Toxics	2. Conflicts	2. Corruption	2. Drinking water
3. Excessive working time	3. Hazards	3. Gender equity		3. Sanitation
4. Wage assessment		4. Human health		4. Children education
5. Poverty				
6. Migrant labor				
7. Freedom of association				
8. Unemployment				
9. Labor laws				

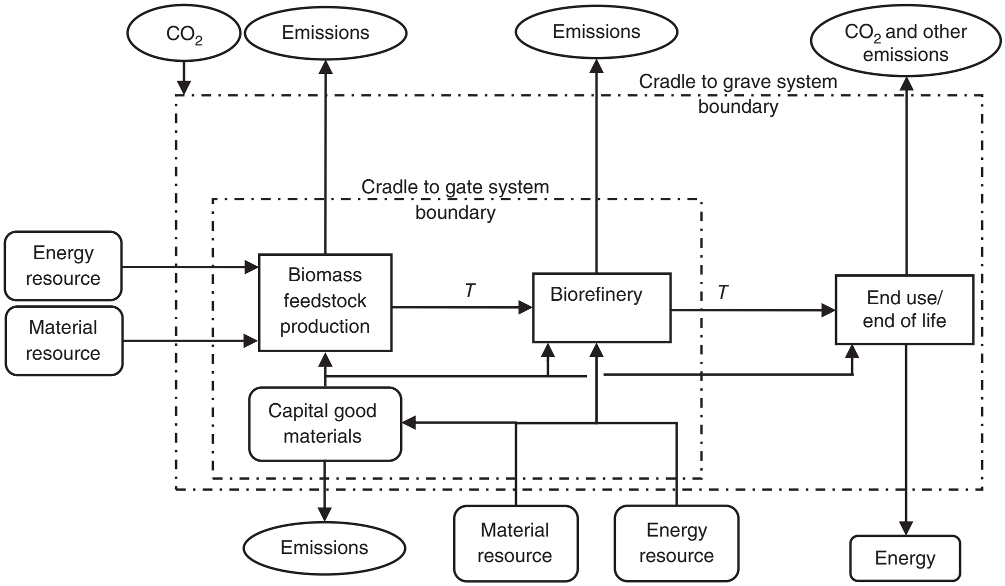


Figure 5.15 *A biorefinery system has biomass production, product manufacturing, end use and construction materials' life cycle process blocks. T shows where the transportation of materials is involved.*

The sequence for annualized costs is different from the sequence for environmental impacts and is shown as follows:

Biomass feedstock > Energy > Raw materials (excluding biomass feedstock) > Capital good raw materials > Emissions

These observations are shown by a generic plot of the environmental impact versus annual added cost of biorefinery systems in Figure 5.16. The cradle to gate biorefinery system has four main loads to analyze for LCA, as follows, shown by numbers 1 to 4 in the figure:

1. Raw materials
2. Energy
3. Capital good raw materials
4. Emissions

Figure 5.16 shows a horizontal line for higher emissions from a fossil based equivalent conversion system that the biorefinery system is designed to replace. The environmental impact from the biorefinery system is shown by the y axis value of point 4. The added cost of production is shown by the x axis value of point 3 or 4 (assuming that emissions do not add cost to the plant). A biorefinery cradle to gate plant may prove to be unsustainable if the target for emission reduction is higher than its current level of emission reduction and if the market price of its products is lower than their added cost of production.

The following lines are thus shown in Figure 5.16:

- Emission from fossil based equivalent product
- Emission reduction target by policy
- Cost of production
- Market price of product

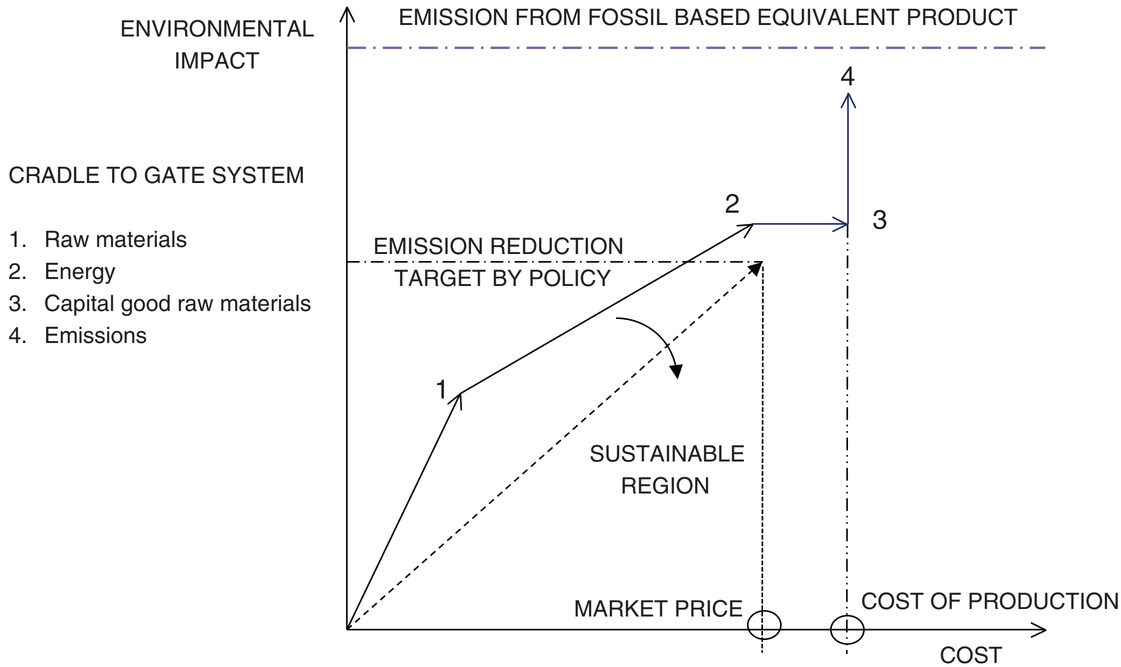


Figure 5.16 *Added cost and environmental impact (contribution analysis) of biorefinery cradle to gate systems.*

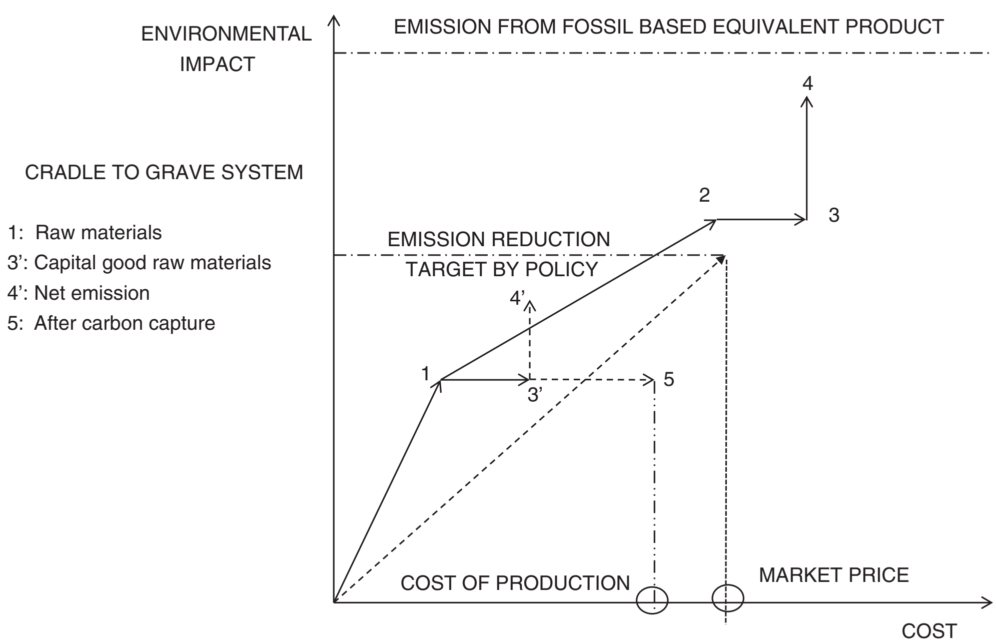


Figure 5.17 *Added cost and environmental impact (contribution analysis) of biorefinery cradle to grave systems.*

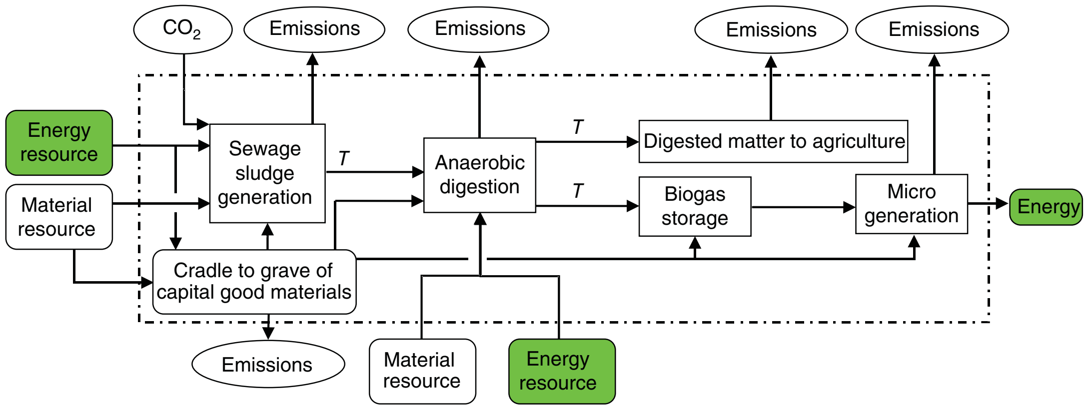


Figure 5.18 *Cradle to grave anaerobic digestion of sewage sludge system for LCA. T stands for transport.*

The target will be to operate the plant below the diagonal and within the lower triangle of the rectangle created by the horizontal line for the "Emission reduction target by policy" and the vertical line for the "Market price" of the product.

A cradle to grave biorefinery system analysis can show a reduction in emissions due to capture of carbon dioxide during biomass production. In addition, the energy balance over the entire cradle to grave system should show net energy production rather than consumption via biomass exploitation. Thus, line 1–2 does not exist in the cradle to grave biorefinery system's added economic value and environmental impact (contribution analysis) profile in Figure 5.17. Line 1–3′ shows the capital good raw material. Line 3′–4′ shows the new net emission after carbon capture (by biomass during production), reduced from line 3–4 for the cradle to gate system. If the entire emission is captured by added investment, line 3′–5 can be created. Therefore, any emission reduction will be accomplished by added costs. The cradle to grave biorefinery system operating at points 4′ and 5, lower than the emission reduction target and product market price, is sustainable.

Further, see the combined economic value and environmental impact analysis calculations in Chapter 7.

Further Challenge Exercise 1. Draw the added cost and environmental impact (contribution analysis) profiles of the following systems in Figures 5.18 to 5.20. Develop hypotheses as necessary.

5.2.2 Socioeconomic Analysis

A socioeconomic analysis is done to estimate the number of job creations and any challenges and barriers associated with an industrial activity. The social performance needs to be compared with other similar systems, in order for an industrial system to operate over the long term. The IChemE provides a metrics to organize the socioeconomic data in the categories of workplace and society:

http://nbis.org/nbisresources/metrics/triple_bottom_line_indicators_process_industries.pdf

These are adaptable to biorefinery systems analysis. Furthermore, the following categories are recommended for biorefinery supply chains.

1. Employment and social well-being: average, highest paid and lowest paid indicative wages and benefit packages
2. Profit as a percentage of payroll expenses
3. External trade
4. Energy security
5. Resource conservation
6. Social acceptability

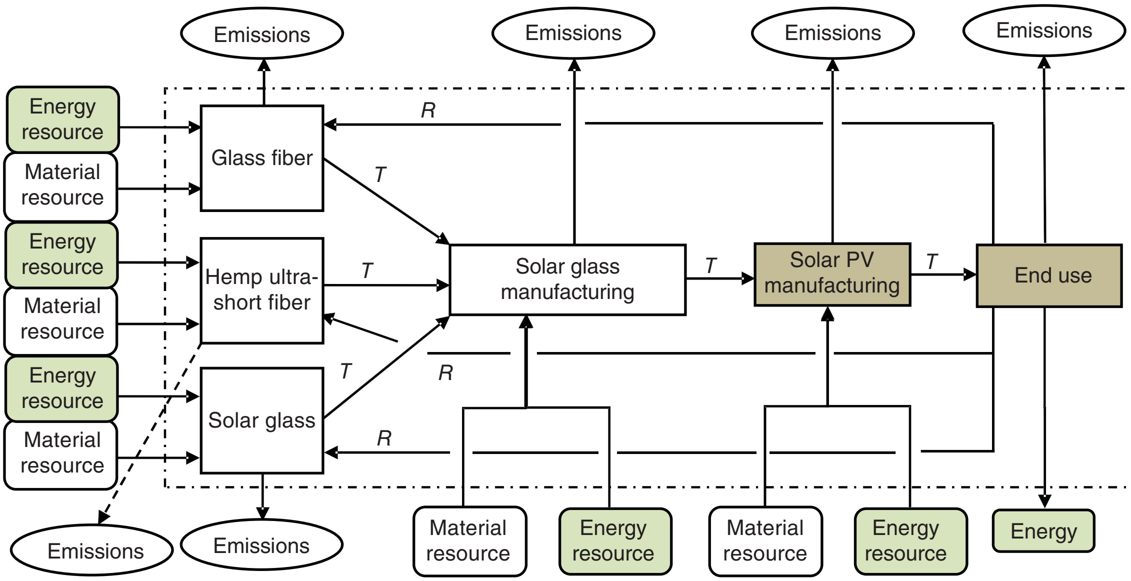


Figure 5.19 Cradle to grave solar organic photovoltaic (OPV) glass manufacturing system for LCA. T stands for transport. R stands for recycle. T and R also cause resource depletion and environmental emissions. Only a part of "Solar PV manufacturing" and "End use" block impacts due to solar glass manufacturing needs to be considered within the system boundary.

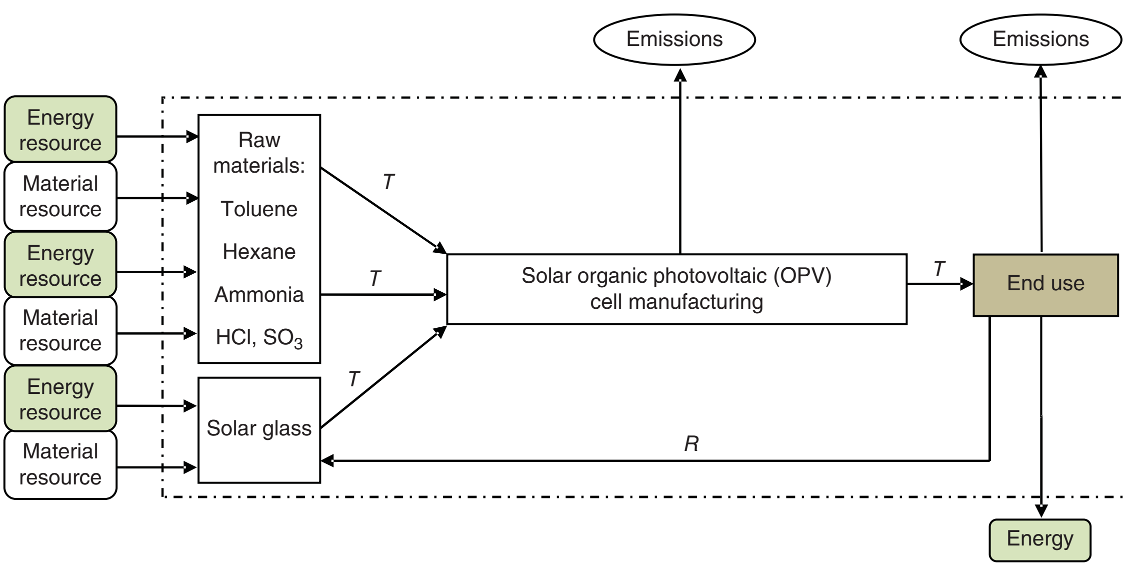


Figure 5.20 Cradle to grave solar OPV cell manufacturing system for LCA. T stands for transport. R stands for recycle. T and R also cause resource depletion and environmental emissions. Only a part of "End use" block impacts due to solar cell manufacturing needs to be considered within the system boundary.

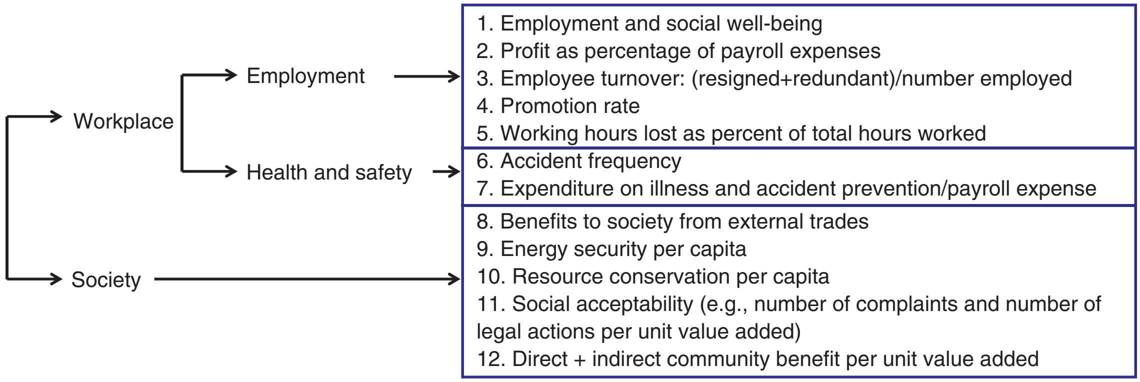


Figure 5.21 *Recommended socioeconomic indicators for biorefinery systems.*

Figure 5.21 shows the recommended structure of the socioeconomic indicators for biorefinery systems.

5.3 Summary

This chapter shows important ways to present LCA results, such that interpretation is accessible. The chapter also outlines multicriteria methods, as well as the incorporation of technoeconomics and socioeconomics in the analysis. Biorefinery sustainability must be assessed using LCA, technoeconomics and socioeconomics. Data uncertainty analysis, sensitivity analysis and Monte Carlo simulations are essential to minimize errors in estimation, to find more important indicators, activity and inventory hot spots. Though these tools are shown to apply for LCA results interpretation, these can also be used for technoeconomic and socioeconomic analyses.

References

1. E. Martinez-Hernandez, M.H. Ibrahim, M. Leach, P. Sinclair, G.M. Campbell, J. Sadhukhan, Environmental sustainability analysis of UK whole-wheat bioethanol and CHP systems, *Biomass Bioenergy*, **50**, 52–64 (2013).
2. *IPCC Guidelines for National Greenhouse Gas Inventories*, Intergovernmental Panel on Climate Change, Geneva, Switzerland, 2006.