Chapter 14
Use of Input–Output Analysis in LCA

Tuomas J. Mattila

Abstract Input–output analysis can be used as a tool for complementing the traditionally process-based life cycle assessment (LCA) with macroeconomic data from the background systems. Properly used, it can result in faster and more accurate LCA. It also provides opportunities for streamlining the LCA inventory collection and focusing resources. This chapter reviews the main uses of input–output analysis (IO) to ensure consistent system boundaries, to evaluate the completeness of an LCA study and to form a basis for in-depth inventory collection. The use of IO as a data source for social and economic sustainability metrics is also discussed, as are the limitations of the approach. All aspects are demonstrated through examples and references both to recent scientific literature and publicly available datasets are provided. The aim of the chapter is to present the basic tools for applying IO in practical LCA studies.

Learning Objectives
After studying this chapter, the reader should be able to:

- Understand the historical background of input–output analysis and how it relates to LCA.
- Understand the basic equations of input–output analysis.
- Use input–output datasets to find background information on product systems and processes.
- Use hybrid input–output analysis to identify hotspots and the effect of cut-off in process-LCA.
- Use input–output analysis to improve process-LCA dataset.

T.J. Mattila (✉)
Finnish Environment Institute SYKE & Luonnonkoneisto
Engineering Co-operative, Helsinki, Finland
e-mail: tuomas.mattila@ymparisto.fi

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- Use input–output analysis as a basis for collecting more detailed process-LCA data.
- Find social and economic data to supplement environmental LCA.
- Understand the strengths and the limitations of using input–output analysis as supplement to process-LCA.

14.1 Introduction

This chapter introduces how to use input–output analysis (IO) in life cycle assessment (LCA). IO was initially developed for macroeconomic systems analysis and planning, but it shares many approaches and methods with process-based LCA. After decades of separate methodological development, the recent trend is to combine the tools into environmentally extended input–output analysis (EEIO), hybrid IO-LCA and comprehensive sustainability assessment. The application of IO together with LCA is assisted by the fact, that it shares the same structure as attributional LCA, linking environmental impacts to economic demand through a product system.

An important problem in conventional process-based LCA is cut-off, or the omission of certain parts of the product system (see Chap. 9). LCA attempts to model every environmental, social and economic impact caused by a product throughout its life cycle from "cradle to grave", integrated over time and space. In practice, this is impossible, and certain simplification for the system boundaries have to be introduced. Everything outside those system boundaries is considered to be "cut-off" from the analysis. If this cut-off is allowed to be subjective, it ruins the idea of comparable and repeatable results. Therefore detailed cut-off criteria, product category rules, standards and handbooks have been developed for standardising and harmonising system boundary setting (EC-JRC 2010).

The product system of an LCA can be thought of as a branching tree. It starts from the functional unit and branches out to the first tier of inputs needed to supply the functionality. Each of these first tier inputs then branches out into second tier inputs and so forth (EC-JRC 2010). This branching out is repeated until all the identified inputs and outputs are either resources extracted or emissions emitted to the environment (i.e. "elementary flows"). In practice, only a part of this branching out is done in an individual study. In a typical study, primary data is collected for the foreground processes, which are closest to the final user (see more about foreground process in Sect. 8.2.3). The remaining inputs are connected to LCA databases, which include product systems from previous studies. This forms the background system. The result is a branching process diagram, which proceeds from an individual product towards more general background processes. In addition, there are processes and flows for which no data can be found, and they are considered cut-off. This dataset is then used to estimate, how much environmental impacts should be allocated to the product system in question. In comparison to this branching bottom-up approach, IO ends up with the same result from the top-down, starting from economy wide statistics and narrowing down to industries and product systems.

The IO-based sustainability assessment does not start from a product, but inventory data are collected at the whole economy level. Then the total environmental, social and economic results are allocated to specific industries. This will give a set of “satellite accounts”, which describe how much direct impacts each sector causes during a year of production. Using economic allocation, these direct impacts are then combined into embodied impacts for each produced good or service (i.e. how much impact is caused by the whole upstream processing of a good or service). This results in a simultaneous IO-based LCA of all the products in the macroeconomic system. The embodied impact intensities for each product or service can then be used to calculate footprints for subsystems of the economy (e.g. countries, sectors, individual consumers).

A key assumption in IO is that the relationship between production and impacts is linear. This same assumption is shared by attributional LCA but not by consequential LCA. The attributional LCA proceeds by attributing a certain share of the global impacts to a product (e.g. “What fraction of airplane emissions is attributed to an air-freight package?”). Consequential LCA estimates the consequences of changing a part of the economy (e.g. “How much do global emissions change in response to one additional package? What if airfreight increases tenfold?”) (see more about attributional and consequential LCA in Sect. 8.5.3). Thus far, attributional LCA has been used much more than consequential LCA. While the consequential approach may be more relevant for decision-making, it also produces nonlinear models which are challenging to integrate with linear models such as IO. As the focus of this chapter is on introducing IO and its applications, the following will include applications to only attributional LCA.

The IO-based approach has two main benefits: it is fast and it is comprehensive. Unlike a process-based LCA, which includes choices about system boundaries and is limited by the resources for inventory collection, an IO-based LCA has the whole economy as its system boundary. It shows indirect and feedback relationships among processes and sectors and is rapid and inexpensive to conduct. Therefore, it is a good screening level tool. In spite of these benefits, it also has several drawbacks. Because IO relies on readily available statistics, the resolution of products is limited by the availability of statistics. This results in aggregation errors when the footprint of “steel products” is used instead of the footprint of “an office chair, of specified make and manufacturer”. In addition, the data is usually at least a few years old, as it takes time for the statistical office to collect and harmonise the data from individual companies. These problems are also present in process-LCA databases, but usually the product disaggregation and technology mixes are more diverse. A major drawback is also the limited coverage of environmental impact categories. Sector specific emissions for toxic substances especially are highly limited compared to the accuracy commonly found in process-LCA databases. Using process-LCA together with IO can utilise the benefits of IO and minimise the problems. In a hybrid-LCA, process-LCA data is used for foreground systems and for reliable process-LCA datasets. IO-LCA is then used to capture all the missing flows. Ideally, this results in a comprehensive system boundary and high data quality.

The structure of the chapter is to first give an outline of IO, starting from the background where it rose from. This gives perspective on the current applications. Then the three main uses of IO in LCA are discussed: filling gaps in process-LCA, providing a first draft template to identify hotspots for process-LCA data collection and using IO as a data source for economic and social sustainability assessment. The approach is practical more than theoretical. Each topic has a worked out example using real data to highlight the use of IO. A more mathematical description of IO and an application to the Finnish economy can be found from the dissertation of the author (Mattila 2013).

14.2 Introductory Examples to Environmentally Extended Input–Output Analysis (EEIO)

The origins of IO are in economic planning and the analysis of multiplier effects. These effects can be demonstrated with a very simple example.

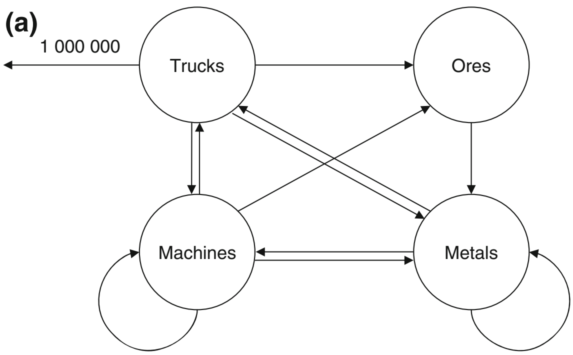
"Assume that a farmer needs to supply 1000 kg of grain. Each 1000 kg of grain requires 30 kg of grain as seed. How much total grain has been produced to supply 1000 kg to a consumer?" This problem presents a loop: the outputs of the process are used as its inputs. This results in an infinite series of tiers in the supply chain. For producing 1000 kg of grain, 30 kg of grain is needed for seed (1st tier), the production of 30 kg of grain requires 0.9 kg of seed (2nd tier), for which 0.027 kg of seed (3rd tier) was needed, etc. As each tier is much smaller than the previous tier, the total amount can be approximated by calculating a few tiers and then adding the results. For an accurate answer, the solution can be found from the input–output relations. If the production of 1000 kg requires 30 kg of seed, the input–output ratio is 30/1000 = 0.03. The net output per unit of production is then 1 − 0.03 = 0.97. The total amount of grain needed for a net output of 1000 kg is then (1/0.97) · 1000 kg = 1030.928 kg. In this case, there is a very small multiplier effect (0.03 units of additional production for each unit of demand). In historical times when yields were lower and part of the grain was used as feed for the working animals, the input–output ratio was much higher and much of the production of grain was used to meet the inputs of producing that grain. In more general terms, the total amount of production $x = y/(1 - a)$, where x is the total amount of production, y is the final demand and a is the input coefficient.

These kinds of feedback loops are simple, when a process uses its own outputs as inputs. The problem becomes more challenging, when a process supplies outputs across the economy and uses inputs from several sources. The same feedback loops are present, but they can cycle through several tiers of production. These delayed feedback loops are very common in complex supply chains (or more accurately supply networks), and make economic planning difficult. The problems of planned economies were what made Wassily Leontief develop input–output analysis. He studied in the USSR and Germany, but later moved to the United States, where the wartime economy and subsequent restructuring of the economy provided a good testing ground and plenty of resources for applying the theory. His work with development of input–output analysis earned him a Nobel prize in economy in 1973.

In order to understand IO, let us look at an imaginary production system in a planned economy (Fig. 14.1). Assume that the goal is to build 1,000,000 trucks, and that needs inputs from four economic sectors: truck manufacture, metal manufacture, machine manufacture and ore mining. The sectors are deeply interconnected with trucks needing inputs from metals and machinery; metals needing metals, machinery and ores; machinery needing metals and machines; and ores needing machinery. In addition, each sector needs trucks to transport goods and raw materials. The system clearly has several feedback loops at different levels. It could be solved stepwise, following each loop until the additional production needed would be very small. In a sense, it reminds us of life cycle assessment and interconnected unit processes. A stepwise approach is feasible, if the system is quite small, but what if the system has thousands of sectors and millions of interactions

Fig. 14.1 The same product system described as a flowchart and an input coefficient matrix (**A**) and final demand vector (**y**)

(a)



(b)

$$
Y = \begin{array}{l} \text{Trucks} \\ \text{Metals} \\ \text{Machines} \\ \text{Ores} \end{array} \begin{bmatrix} 1\,000\,000 \\ 0 \\ 0 \\ 0 \end{bmatrix}
$$

$$
A = \begin{array}{l} \\ \text{Trucks} \\ \text{Metals} \\ \text{Machines} \\ \text{Ores} \end{array} \begin{array}{c} \begin{array}{cccc} \text{Trucks} & \text{Metals} & \text{Machines} & \text{Ores} \end{array} \\ \begin{bmatrix} 0 & 0.02 & 0.02 & 0.05 \\ 0.15 & 0.2 & 0.2 & 0 \\ 0.2 & 0.1 & 0.2 & 0.4 \\ 0 & 0.1 & 0 & 0 \end{bmatrix} \end{array}
$$

like the world economy? Fortunately, the solution is almost as simple as in the case of the grain and seed, and almost all of IO can be summarised in a single equation.

The economic system can be described by using an input coefficient table (**A** in Fig. 14.1). Each column represents a sector, showing the inputs needed to produce one unit of output from that sector. For example, it takes 0.1 units of ores to make one unit of metals in the imaginary truck example. The outputs from the economic system are accounted separately in a final demand vector (**y**). It does not matter what the units are, although commonly a single unit of monetary value is used for each sector.

Now the total amount of produced goods (**x**) is the sum of final demand **y** and the amount of production needed for intermediate demand (i.e. for making all the intermediate products needed to supply the final product). The amount of intermediate production is in direct relation to the total production in each sector (**x**) and the amount of intermediate inputs each sector needs from other sectors. Written as an equation:

$$\boldsymbol{x} = \boldsymbol{y} + \boldsymbol{A}\boldsymbol{x} \tag{14.1}$$

If we have only a single sector, this results in the same solution as in the grain example: $x = y/(1 - a)$. When there are several sectors, the structure of the equation is the same but matrix inversion replaces scalar division. This gives the core equation of economic input–output analysis:

$$\boldsymbol{x} = (\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{y} \tag{14.2}$$

where **I** is an identity matrix, which has ones on the diagonal and zeros elsewhere. In linear algebra, it has the same role as one in scalar algebra. $(\mathbf{I} - \mathbf{A})^{-1}$ is the inverse of $(\mathbf{I} - \mathbf{A})$, which can be thought of as the equivalent of division in matrix algebra. (The example can be followed in a spreadsheet program by using the functions MMULT() for matrix multiplication and MINVERSE() for inversion). This inverse of the input coefficient table is commonly known as the Leontief inverse, and it shows the system wide interconnections of each sector with other sectors in its supply chain.

Applying Eq. (14.2) to the system in Fig. 14.1 gives a solution to the truck problem (Fig. 14.2). In order to produce 1,000,000 trucks for final demand, 1,012,608 trucks need to be manufactured. The elements of $(\mathbf{I} - \mathbf{A})^{-1}$ describe the total production needed to provide one unit of final demand from the sector. These are often called indirect multipliers. For example, it takes 0.26 units of metals to produce a truck, while the direct input (**A** matrix in Fig. 14.1) is only 0.15. The indirect inputs take into account all the feedback loops in the system and are always bigger than the direct inputs.

However, how does this relate to sustainability assessment, since many of the "sustainability aspects" are externalities or outside the economic sectors? This has been solved through the introduction of "satellite accounts" and environmental extensions, thus resulting in an environmentally extended input–output table

$$\underbrace{\begin{bmatrix}1\,012\,608\\ 264/34\\ 299\,480\\ 26\,473\end{bmatrix}}_{X} = \begin{array}{cc} & \begin{array}{cccc}\text{Trucks} & \text{Metals} & \text{Machines} & \text{Ores}\end{array}\\ \begin{array}{c}\text{Trucks}\\ \text{Metals}\\ \text{Machines}\\ \text{Ores}\end{array} & \underbrace{\begin{bmatrix}1.01 & 0.04 & 0.03 & 0.06\\ 0.26 & 1.32 & 0.34 & 0.15\\ 0.3 & 0.24 & 1.32 & 0.54\\ 0.03 & 0.13 & 0.03 & 1.01\end{bmatrix}}_{(\text{I-A})^{-1}}\end{array} \underbrace{\begin{bmatrix}1\,000\,000\\ 0\\ 0\\ 0\end{bmatrix}}_{Y}$$

Fig. 14.2 A linear algebra solution to the system in Fig. 14.1

(EEIO). The environmental extension describes how much emissions or resources are used for each unit of production on a sector. These "direct emission intensities" are often collected as part of national statistics, especially for greenhouse gases and energy consumption. While the extension may sound difficult, it makes only minor additions to Eq. (14.2):

$$\boldsymbol{g} = \boldsymbol{Bx} = \boldsymbol{B}(\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{y} \tag{14.3}$$

where **g** is a vector of embodied environmental impacts associated with final demand **y**, and **B** is a matrix of direct environmental impact multipliers for each sector.

If we were interested in land use and assume that the manufacturing sectors each require 0.01 m^2 of land area and mining requires 1.0 m^2 of land area (i.e. B = [0.01 0.01 0.01 1.0]), the total land area demand of the truck example is **g** = 0.01 1,012,608 + 0.01 · 264,734 + 0.01 · 299,480 + 1.0 · 26,473 = 42,241 m^2, with 26,473 m^2 or 63% coming from the mining sector.

The same equation can also be written in a different form:

$$\boldsymbol{g} = \boldsymbol{Bx} = \boldsymbol{B}(\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{y} = \boldsymbol{Cy} \tag{14.4}$$

where **C** is a matrix of embodied environmental impact intensity (impact/monetary unit) for all products in the system. It can be thought of as a life cycle inventory (LCI) dataset and is a very valuable in constructing hybrid LCAs and making first estimates for products and services for which process-LCA data is hard to find (e.g. insurance services).

This simple example contains all the basic elements of EEIO and IO, which are used in all common applications of input–output analysis ranging from product level to societal level. However, the example is deceptively simple, the actual usefulness of IO becomes more obvious when one uses a real world example.

Example 14.1 Compare Danish and Chinese steel industry inputs from WIOD datasets 2000 and 2008. Look at total volume of inputs, direct input coefficients and indirect input coefficients.

The WIOD (World Input–Output Database) is one of the publicly available multiple region input–output (MRIO) datasets. It is available from wiod.org. The dataset includes both the input–output tables as well as the socio-economic and environmental accounts. For this example, we will have a look at the monetary input–output table and derive the direct and indirect inputs for Danish and Chinese steel industries.

The WIOT (world input–output table) is arranged in a sector-by-sector format, with all the sectors for a given country in one unit (Fig. 14.3). For the excel file, the country code and sector codes for Danish steel are DNK 27t28 "Basic metals and fabricated metal". In the spreadsheet, the total output (**x** vector) is the last of the columns and was \$5753 M in year 2000 and \$13 141 M in 2008. For Chinese steel production (CHN 27t28), the output was \$211,880 M in 2000 and \$1,251,139 M in 2008. Therefore, the Chinese metal production is considerably larger than the Danish and is growing at a rapid pace. However, has the production technology changed as well?

The emissions of a sector can be considered from a production and life cycle perspective. For the production perspective, a key indicator is the direct emission intensity, which describes the fuel consumption of that sector per monetary unit of output. The direct emission intensity of Chinese metal production has decreased. In 2000, the emissions were 272 Mt CO_2 (1.28 kg CO_2/\$) and in 2008 they were 578 Mt CO_2 (0.46 kg CO_2/\$). For Danish metal industry, the corresponding figures were 0.4 Mt CO_2 (0.07 kg CO_2/\$) in 2000 and 0.4 Mt CO_2 (0.03 kg CO_2/\$) in 2008. Both industries had obtained considerable reductions in emission intensity, but was this at the cost of increased outsourcing and more embodied emissions in the inputs? For this, we need the life cycle perspective of a sector level carbon footprint.

A first step in calculating the carbon footprint is to convert the monetary flow data into input coefficients (i.e. how much inputs are needed to provide one unit of output; the **A** matrix). This is obtained by dividing each column j of the monetary flows by the corresponding total output (x_j). (In this case, the **x** contains zero elements reflecting that some of the sectors are not active in the country, which results in an error. This can be avoided by replacing the zeros with a very small number such as 1/1000,000,000.) The input coefficients can be used for a rough

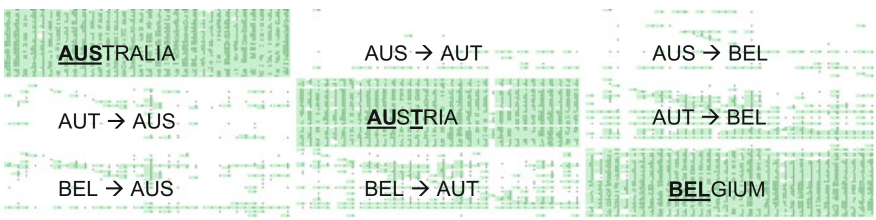


Fig. 14.3 A screenshot from a subset of the WIOT table from WIOD-database. Intra-country transactions are on the diagonal, while trade between countries is arranged on a grid. Each country has 35 sectors

comparison of the value added and input intensity of the sectors. The sum of all input coefficients for Danish steel in 2000 was 0.55 and for Chinese steel it was 0.77. This indicated that the Danish steel industry was able to produce more value added (i.e. less inputs needed for outputs produced) for each unit than Chinese. By 2008, the input coefficients for the industries had increased further to 0.62 for Denmark and 0.80 for China. This indicated that the industries had outsourced their input production to other sectors or countries and/or moved to lower refinement value products.

The trend to outsourcing can be seen from the highest input coefficients (Table 14.1). For both countries, the Basis Metals and Fabricated Metal sector has a considerable amount of inputs from companies within itself. In addition, China has its own mining operations and imports ores from Australia (input coefficient increased by 140% from 2000 to 2008). In contrast, the Danish steel industry has most of its purchases from retail and wholesaletrade services, and imports mainly processed metals from Germany. The largest change in the Danish steel industry has been the increase of recycling (input coefficient change of 100%).

The monetary inputs are interesting, but as we are interested in the carbon footprint, a few more stages are necessary. The first stage involves calculating the Leontief inverse $(\mathbf{I} - \mathbf{A})^{-1}$. The identity matrix **I** can be constructed in a spreadsheet by defining a table, where the elements are set to 1 if the row and the column have the same index [i.e. (1,1) or (2,2)] and 0 elsewhere. After this each element of **A** is subtracted from the corresponding element of **I** and the resulting matrix is inverted (MINVERSE() function in spreadsheet programs). For the WIOD, the inversion will take a lot of memory and some time on most desktop computers. Closing additional programs and copying **I** and **A** matrices to a new spreadsheet document will help conserve memory. After the inversion, it makes sense to copy the inverted matrix to a new spreadsheet to avoid the program from repeating the calculation every time the document is changed.

Table 14.1 A comparison of top 5 direct input coefficients of Chinese and Danish steel products in 2000 and 2008

Sector	Country	In 2000	In 2008	Change (%)
Input coefficient—China basic metals				
Basic metals and fabricated metal	CHN	0.33	0.33	1
Mining and quarrying	CHN	0.07	0.09	29
Electricity, gas and water supply	CHN	0.04	0.05	25
Machinery, nec	CHN	0.02	0.03	50
Mining and quarrying	AUS	0.01	0.02	140
Input coefficient—Denmark basic metals				
Wholesale trade and commission trade	DNK	0.06	0.08	33
Basic metals and fabricated metal	DNK	0.07	0.06	−14
Basic metals and fabricated metal	DEU	0.05	0.07	40
Retail trade	DNK	0.03	0.03	0
Manufacturing, nec; recycling	DNK	0.01	0.02	100

The second stage involves some manual work (or macro programming) in collecting the emissions for each sector in the economy. The CO_2 emissions for each sector in each country have to be collected into a column, which has the same ordering as the sectors and countries in the input–output table. The WIOD has this dataset arranged in separate files for each country, which means that the files need to be combined. After this step, the emissions are divided by the corresponding total output $\mathbf{x}$ to yield the $\mathbf{B}$ matrix (in this case we have only CO_2 emissions, so it is a vector instead of a matrix). After this the $\mathbf{B}$ matrix is arranged to be vertical (a row vector, using TRANSPOSE() function) and is multiplied with the $(\mathbf{I} - \mathbf{A})^{-1}$ matrix (MMULT() function). The result is a row vector, which contains the carbonfootprint of all the products in the world ($\mathbf{C}$ matrix). It is a very useful dataset for recalculation of the examples in this chapter and in other applications.

For Chinese metal products in 2008, the carbon footprint was 2.20 kg CO_2/\$, or almost five times the direct emission intensity. For Danish metal products, the carbon footprint was 0.32 kg CO_2/\$ or almost ten times the direct emission intensity. Both industries have most of their carbon emissions in the supply chain. A first step in locating those emissions is multiplying the input coefficients of the sectors (in $\mathbf{A}$ matrix) with the carbon footprint intensities to have a look, which inputs have the highest embodied emissions.

For Denmark, the emissions diverge globally at the first tier of the supply chain (Table 14.2). The top 5 embodied emissions include metal products from Germany, Russia, Denmark and Rest of the World (RoW; a statistical grouping of economies which were not included in the detailed country analysis of WIOD). If a top 20 listing of emissions had shown, it would have included several more countries in and outside Europe. In contrast, the Chinese metal production has its supply chain focused in China. Most of the inputs were energy, machinery and raw materials for metal production.

Although the metal product sectors of China and Denmark are so different that direct comparison is not meaningful, they provided an example of the use of EEIO to learn about global supply chains and their technological differences. This example also serves as a kind of a warning for using EEIO results in LCA without looking at the product mix in the sector. Using the Chinese industry average for a finished metal product would probably result in a major overestimation of the impact.

Table 14.2 The inputs with the highest share of the carbon footprint of the basic metals sectors in Denmark and China in 2008

	Denmark	kg CO_2e/\$		China	kg CO_2e/\$
Direct emission		0.03	Direct emission		0.46
Basic metals	DEU	0.04	Basic metals	CHN	0.74
Basic metals	RoW	0.02	Electricity	CHN	0.49
Basic metals	RUS	0.02	Mining	CHN	0.16
Basic metals	DNK	0.02	Non-metallic mineral	CHN	0.05
Electricity	DNK	0.01	Machinery	CHN	0.05
Total upstream		0.28	Total upstream		1.73

14.3 Avoiding Cut-Off Through Comprehensive System Boundaries

Most modern supply chains branch out globally, as was seen in the example of Danish metal products. Collecting process-LCA data on a supply chain, which rapidly spreads over several countries and continents, is difficult. Also wholesale and retail trade, which may cover 10–20% of all the inputs to a product manufacturing, often have no process-LCA datasets. The practical consequence of global supply chains and a shift to more services is an increase of cut-off in process-LCA.

Cut-off has always been unavoidable. Usually, it was assumed that the cut-off flows would be insignificant, but later studies have shown that the omission is often 30% or even much larger in some impact categories (Suh et al. 2004).

In principle, there are two sources of cut-off: the identified cut-off and the non-identified cut-off. The identified cut-off consists of flows that are identified during the process-LCA, but which have no LCI data available. The unidentified cut-off is flows which are omitted, since they are intangible (not related to energy or material flows) or simply overlooked. A real-life example of the latter would be ignoring maintenance services in a pulp and paper mill, although the maintenance services consume tools and specialty metals, with considerable impacts to metal depletion (Mattila 2013). Other classical examples would be ignoring insurance, facility rent, retail trade, marketing or software development. Although they may be below a specified cut-off limit at each stage, if these are omitted in all parts of the process-LCA product system, the complete omission will be significant. If economic or social indicators are considered, the omission will be even larger. In a case study of smartphone sustainability assessment, much of embodied child labour was in trade services and warehouse work in developing countries in the parts of the supply chain that supplied parts for smartphone assembly. This came as a surprise both to the analysts and the social responsibility people of the smartphone manufacturers, wholesale trade had previously been ignored in the inventory for child labour.

Fortunately, IO can be used to estimate both identified and non-identified cut-off flows. The first case is termed missing inventories and the second is termed checking for completeness. Both are applications of so-called hybrid-LCA. For a more detailed description of different ways of constructing a hybrid-LCA, see (Suh and Huppes 2005).

A critique for using the IO dataset to fill gaps is that it usually contains very few LCIA impact categories, most often climate impacts from fossil fuels. However, for some types of products and technologies there is a strong correlation between this category and many other LCIA impact categories (excluding toxic impacts and land use) (Laurent et al. 2012), so one approach is to use the ratio of process-LCA climate impact to cut-off impact as a "correction factor" or estimate of cut-off magnitude.

14.3.1 Estimating Missing Inventories from IO Data

Process-LCA has traditionally focused on physical processes and products. Consequently most LCA databases lack services. It is quite straightforward to complete these missing inventory items by using input–output results in a tiered analysis. The analysis consists of four stages:

1. Convert physical flows to monetary flows using price data or for example import statistics, which report both mass and price flows
2. Find an appropriate IO dataset (good geographical and year coverage, relevant environmental extensions included)
3. Convert consumer prices to producer prices (by removing value added tax as well astrade and transport margins)
4. Convert the monetary flow to the currency and year of the IO dataset using producer price indexes
5. Multiply the monetary flows with the corresponding LCI results from the IO dataset (matrix **C** in Eq. 14.4).

It is easiest to describe this process again through an example.

Example 14.2 Estimate the carbon footprint for a wedding trip planned to be from Denmark to San Francisco. The planned flight distance is 18,000 km, some estimated costs would be \$40 for public transportation, \$3000 for hotels and \$1000 for restaurants and \$100 for travel insurance.

Assuming that the emission intensity of airplane travel is 0.11 kg CO_2-eq/tkm (ecoinvent 2.2), the climate impact of the flight would be 3960 kg CO_2-eq. We will use the USEIO-LCA model for the economic flows (www.eiolca.net). The EIO-LCA model has a base year of 2002 both in producers and purchasers prices. For the purposes of this example, we will use the purchasers price model, which avoids translating the prices to producers prices (for now).

In order to use the model the prices have to be converted to year 2002 prices. This can be achieved through the detailed consumer price indexes (CPI), available from the US Bureau of Labor Statistics (www.bls.gov). Finding the right statistical category for each commodity requires some research and guesswork. For this example the CPI are presented in Table 14.3. Since prices have increased considerably from year 2002, the purchases of \$4440 in 2014 would have been only \$3265 in 2002.

Using the converted prices, the carbon intensities from the EIO-LCA can be used to calculate the carbon footprint from the monetary flows (Table 14.3). Based on the results the overall footprint associated with the monetary flows would be 1844 kg CO_2-eq, thus, compared to the emissions from the flight (3960 kg CO_2-eq) the emissions of the monetary flows would be considerable. The major contributor is the stay at the hotel, contributing 1367 kg CO_2-eq. The EIO-LCA presents a detailed description of the components for each of the carbon footprints. In the case of hotels, the main contribution is from the power generation and supply sector (59%), followed by direct emissions from hotel heating (14%).

Table 14.3 Commodity price indexes for 2014 and 2002 for the four goods in the example, their carbon intensities and the contribution to the overall carbon footprint (excluding the flight)

Commodity	CPI 2014	CPI 2002	Purchase in 2014	In 2002 prices	Carbon intensity (kg CO_2-eq/ $\$_{2002}$)	Carbon footprint (kg CO_2-eq)
Taxi	297	184	$40	$25	1.870	46
Hotels	308	251	$3000	$2445	0.559	1367
Restaurants	155	113	$1000	$729	0.580	423
Insurance	318	211	$100	$66	0.117	8
Total			$4440	$3265		1844

Based on the quick calculation, a good leverage point for reducing the emissions of the trip would be choosing a hotel with high energy efficiency and renewable energy. However, this example has two oversimplifications: first of all the process-based inventory for the flight probably has cut-off, so it represents an underestimation of the total impact; second, the emissions which occur high in the atmosphere have a larger radiative forcing than those close to the ground (therefore the contribution of the other purchases to the whole impact are probably less than the example indicates, and it would be best to avoid the flight altogether).

Example 14.3 The EIO-LCA dataset used in Example 14.2 is quite old (2002). How much would the results change if WIOD year 2008 data would be used instead?

Let us repeat the calculation, but with a different base year (2008) and with producer's prices, since WIOD is based on those. For the conversion from purchasers' to producers' prices, we will just remove the California sales tax (9%), by dividing the costs with 1.09. Since none of the purchases included transportation or retailtrade, we avoided the difficulty of finding the statistics for those.

The results are presented in Table 14.4. Based on the results, the carbonfootprint for the monetary flows would be 1291 kg CO_2-eq, much lower than with EIO-LCA but still significant. The main reasons for the difference are the reduced emission intensity from 2002 to 2008 and the aggregation errors introduced by the WIOD dataset. The EIO-LCA has 428 sectors, with a very detailed disaggregation.

Table 14.4 Commodity price indexes for 2014 and 2002, correction to producers' prices and the carbon footprint using WIOD 2008 data

Commodity	CPI 2014	CPI 2008	Purchase in 2014	In 2002 producers prices	Carbon intensity (kg CO_2-eq/$\$_{2002}$)	Carbon footprint (kg CO_2-eq)
Taxi	297	240	$40	$30	0.75	24
Hotels	308	301	$3000	$2690	0.33	968
Restaurants	155	135	$1000	$799	0.33	287
Insurance	318	271	$100	$78	0.14	12
Total			$4440	$3597		1291

In comparison, the WIOD only has 35 sectors for each country. Consequently, restaurant and hotel services are in the same category and have the same emission factor. Similar aggregation errors are common in the WIOD dataset in all supply chains, resulting in a more "blurry" image of the supply chain and its hotspots.

14.3.2 Estimating Completeness of the Process-LCA Dataset

Input–output can be useful for finding inventory data on flows that are commonly not found in process-LCA databases, such as insurance, financial services and hotels. However, it can also be used to estimate, how complete the process-LCA dataset is. This is based on estimating the input coefficient and value added in the process-LCA dataset. In Example 14.1, the Danish and Chinese basic metal industries were compared, and it was found that the Danish industry has a much lower sum of input coefficients (0.62) than the Chinese (0.8). It means that for each unit of production, the Danish industry produced value added for 0.38 units. If one calculates the input coefficients and value added for a process-LCA dataset and finds that the value added would be much higher (e.g. 0.9 units per unit of production) it either indicates a very profitable process, or much more likely an omission of some important costs (e.g. infrastructure rent, repairs, insurance and transport).

In constructing a process-LCA, it is straightforward to get financial data for the foreground processes, as one is collecting primary data from companies in any case. However, it may be much more difficult to collect financial data from the companies in the supply chain, since they are most likely not willing to reveal their production cost breakdown to a purchaser of their products. In this case, the input coefficients of the IO-table can be used as a template. The list of physical inputs from an LCA unit process database can be compared with the amounts found in the IO-table inputs, taking note of the main differences in inputs in the two datasets. The IO-table inputs can also be circulated to the companies providing the data with a questionnaire, so they can indicate if their inputs differ considerably from the industry average inputs (this can also be a benchmarking process for the participating companies, increasing their interest for participation).

A third approach for estimating the completeness of the process-LCA is to compare the carbon footprint composition between the process-LCA and the sector average carbon footprint. The formal tools for doing this are contribution analysis and structural path analysis (SPA). Contribution analysis maps out the location of direct emissions in the supply network, which contribute the most to the life cycle impacts. Structural path analysis converts the matrix representation of an IO-LCA into a description of process flows, which cause most of the impacts. The full details for these methods can be found in Heijungs and Suh (2002), but they are also incorporated into most LCA software. For the IO dataset, the EIO-LCA has a contribution analysis included in the toolbox and some IO datasets can be imported into LCA software. If neither case is applicable, one has to follow the approach presented in Example 14.1 (i.e. calculate the carbon footprint matrix **C** and multiply the elements of **A** with it to give a first tier breakdown of the supply chain). If the IO-LCA-based results show a significant carbon footprint from trade services, they probably should be included in the process-LCA inventory.

A problem in this straightforward approach is the lack of environmental extensions in IO-LCA. A given input might be highly significant for a single impact category (for example repair services for metal depletion), but if the impact category is not included in the IO dataset, it will not be identified as important. This problem will gradually be resolved as more impact categories are included in environmentally extended input–output (EEIO) models. The process is now underway in impacts related to land use and biodiversity, hopefully sometime soon global inventories for toxic emissions would be published.

14.3.3 Using Input–Output Analysis as a Template for LCA

Thus far, we have been discussing how to use IO-LCA to fill the gaps in process-LCA. However, the process may be reversed: start from IO-LCA and focus the process-LCI collection work on the parts of the IO-product system, which have the highest environmental impacts. This approach is known as the path exchange method (Lenzen and Crawford 2009). It is a highly effective way of collecting LCI inventories.

In practice, one performs a so-called Accumulative Structural Path Analysis (ASPA) (Suh and Heijungs 2007). The ASPA is conceptually simple: one multiplies all the direct inputs (**A** matrix) with the corresponding embodied impact intensities (**C** matrix). Then top ranking inputs are screened to the next step based on either a specified cut-off level (e.g. more than 1% of total impact) or a specified inclusion limit (together the included inputs must cover >90% of total impact). After the screening, the process is repeated for each of the selected inputs for the second tier. This results in a branching tree structure of the process system, which can be visualised with a Sankey diagram or a flow chart (Fig. 14.4). After the path analysis has extracted the most critical pathways, process-LCA is used to check how much the actual inputs in the foreground system differ from those assumed in the IO-table. Then the LCA proceeds by replacing the most critical inputs with process-LCA collected inventory data.

LCA software (such as SimaPro or OpenLCA) includes tools for drawing Sankey diagrams. If the IO dataset has been imported to the software, the path exchange method is straightforward (for import of IO data the reader is referred to instructional material for the respective LCA software). There is however a hidden risk in this simplicity. With the software, it is easy to overwrite the background IO data with the process-LCA which is collected. Because IO systems are so interconnected, this results in the change of every background process. For example, let us assume the studied product is in the basic chemicals sector, and electricity use is a critical input. If the process-LCI result for electricity consumption is much lower, we need to change the default from the IO. If we just replace the input coefficient in the identified process, we automatically change the amount of electricity needed in all the companies in the basic chemicals sector! This will influence all the inputs for the product system, for example, the packaging materials probably needed cardboard, which needed some basic chemicals to manufacture. Therefore, it is important to make copies of the identified processes before changing them.

It is possible to do the whole process manually in a spreadsheet (although using a mathematical programming language will make the work less tedious). The following example presents a simple iteration in carbon footprinting for a new product.

Example 14.4 Using IO to create a template LCA system boundary for an underwater exploration robot. The OpenROV is an open sourced underwater exploration robot kit.

The bill of materials and the estimated costs are found in the project web page (www.openrov.org). For the purposes of this example, the bill of materials of 35 items was aggregated to IO classifications (Table 14.5). From this onwards, the analysis proceeded by calculating the carbon footprint (using WIOD 2008) for each of the materials, ranking the results, choosing a new set of inputs for the second tier and repeating. In each tier, the input coefficients in the **A** matrix were multiplied with the monetary flow of the inputs from that sector. For example: $141 were from the rubber and plastics sector, which had an input coefficient of 0.22 for "Chemicals and chemical products". Therefore, the input coefficients for the chemicals sector were multiplied with $31.

Using a coarse cut-off limit of 5% of the total footprint, the following diagram was obtained in 30 min using spreadsheet software and drawing tools (Fig. 14.4). It highlights that from the bill of materials, the electronics, plastics and metals are the most relevant. Within the electronics supply chain, there are three components that should be investigated in detail: supply of basic metals, electricity and imported electronics. Within the plastic parts, inputs from chemical industry should be investigated, as should the electricity use. For metals, the direct emissions of metal manufacturing and the metal product inputs should be investigated. The only third tier input included (and it was just at the margin of 5% cut-off) was the direct emissions from the chemical manufacture needed for the plastic components.

Overall, the identified processes cover only 52% of the total footprint. Repeating the analysis with a lower cut-off limit (e.g. 1%) would result in a significantly higher number of highlighted processes.

Even with the coarse cut-off limit, the IO-based template seems reasonable. The main identified inputs were similar to what would have been identified using a

Table 14.5 A cost breakdown for the OpenROV 2.7 underwater exploration robot classified to WIOD IO-sector classes. For simplicity, it was assumed all purchases would be from USA

Input	Cost
Electronic and optical equipment	$313
Rubber and plastics	$141
Basic metals and fabricated metals	$56
Manufacturing, unspecified	$6

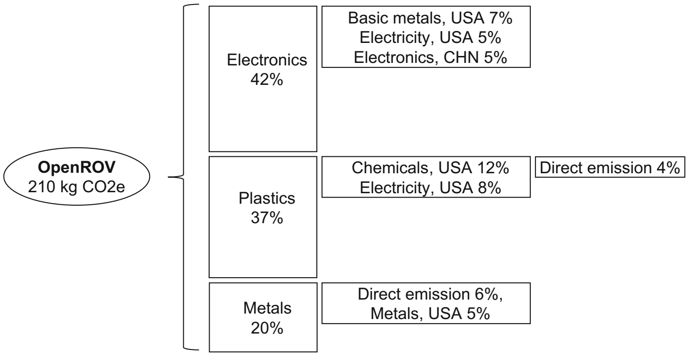


Fig. 14.4 A first estimate of the critical parts of the supply chain for an underwater exploration robot prototype using WIOD data and accumulative structural path analysis with a cut-off of 5%

process-LCA, but having a relative importance score added to them assists in priority setting for further inventory collection.

14.4 Using IO as a Source for Social and Economic Sustainability Assessment

While few IO datasets include many indicators on environment, almost all of them have detailed socio-economic accounts. This can be used as a comprehensive background dataset for social and economic sustainability assessment.

All national accounts include data on employment and value added. Some include the employment by worker category (gender, age and salary level). This can be used to find data for triple bottom line sustainability assessment (see Chap. 5), mapping out where economic activities are happening, where added value goes to and what kinds of salaries are paid to maintain and create the product system.

For example, the WIOD dataset includes the number of employees and the number of persons engaged, and the hours worked by these people and the amount of compensation paid. In addition, it includes a disaggregated dataset for high-medium and low-skilled labour (hours worked and compensation paid). This data can be used to map out, where in the product system work is being done, and the fairness of the compensation compared to the rest of the value added. Average pay in a given country or region is also straightforward to calculate from the data in order to facilitate interpretation.

The social hotspots database (SHDB, socialhotspot.org) has taken this analysis a step further. The database includes inventory and characterisation matrices for social issues (see more about Social LCA in Chap. 16). They are based on risks associated with worker conditions in a given country and sector. These are then used to multiply the hours worked in the supply chain in each sector and country to give an overall risk score for social sustainability, as well as individual indicator (137 indicators) and risk score results (134 risk scores). As more characterisation models become available for social life cycle assessment, there is increased opportunity to use them together with IO-LCA.

One of the benefits of using LCA and IO together is that the analytical tools created for LCA are also applicable to the IO datasets. It is as straightforward to do structural path analysis or a contribution diagram for employment or employee compensation as it is for climate impacts. For example, using the example of the underwater robot the work hour footprint is 13.27 h of work, with the majority of it being 8 h in the electronics supply chain. Of that embodied work, 2.5 h were in USA and 1.4 in the Chinese electronics sector. Approximately 45% of workers in the Chinese electronics sector were low-skilled and 8% were high skilled in 2008. The manufacture of components created some knowledge intensive work, which might be considered beneficial. The value added per hour worked in that sector was 4.7 $/h, of which 33% was wages (labour compensation), equalling 1.6 $/h wages. This is in line with the average manufacturing wages in 2008 in China (Bureau of Labor Statistics, USA), so the sector pays average wage. The calculation could be taken further, by using structural path analysis to map out the entire value tree and the hours worked and the wages paid. These could then be compared to the average wages in the country to evaluate whether the operation is increasing the average wages in the country.

The analysis presented above is based on average statistics. This is a limitation for companies that have a strong policy of social responsibility in the supply chain, as their suppliers might be very different from the overall average figure. For those cases, the benefit of this kind of analysis is to provide a checklist of potential hotspots and to make sure these are addressed in choosing suppliers and negotiating policies.

As the tools for social LCA become more widespread and sophisticated, the IO dataset provide a testing ground for using them. Relatively simple calculations can reveal valuable information about the amount and wages of workers. Complemented with other statistics collected for example by the United Nations International Labour Organization, the analysis can be taken deeper and more focused on issues such as work injuries or child labour.

14.5 Data Sources

14.5.1 Publicly Available EEIO Datasets

There are several publicly available EEIO datasets (Table 14.6), many of them are available for free through an academic license. The datasets however differ in the amount of regions they cover, their sector disaggregation and number of impact categories.

Table 14.6 A comparison of publicly available EEIO datasets

Database	Latest data year	Time series	Regions	Sectors	Impact categories
WIOD	2009	x	40	35	6
EIO-LCA	2002		1	428	20
EXIOBASE 2.0	2007		48	163	98
Waste input–output	2000		1	103	4
EORA	2011	x	190	Average 85	10
CEDA 4.0	2002		6	428	12

The WIOD (www.wiod.org) introduced in the examples of this chapter is a simple to use, relatively small and compact EEIO database. It has a resolution of 40 regions and 35 sectors, which makes it very aggregated and prone to aggregation errors. It also has very few impact categories (6).

In comparison, the EORA (www.worldmrio.com) has a much higher resolution for sectors (on average 85 but ranging from 25 to 428 depending on country) and regions (190 regions). In spite of extensive disaggregation of emission types and sources, the database includes only greenhouse gases, energy, ecological footprint, human appropriation of net primary production (HANPP) and some resource extraction impacts. The cost of a larger sector and country disaggregation is also that the full resolution multiple region input–output analysis (MRIO) cannot be processed with a spreadsheet, but has to be operated through a mathematical programming language (e.g. MATLAB or R). EORA however has a large amount of footprint results precalculated and it has time series of the data, improving analysis possibilities further.

EIO-LCA (www.eio-lca.net) contains some other datasets, but the core dataset is an input–output table of the US in 2002. The resolution is considerable with 428 sectors and the amount of impact categories (the LCIA method TRACI is used) is fairly high for an EEIO model. The web interface (www.eio-lca.net) makes using the tool relatively easy.

CEDA 4.0 (www.cedainformation.net) is based on the same data as EIO-LCA but is much more detailed on the environmental emissions. It has 14 pre-characterised impact categories and 2500 emission and resource depletion categories (LCI inventory level). Currently CEDA 4.0 is available for 6 countries, but the version 5.0 is planned to have global coverage.

The Waste Input–Output Table is a single country input–output table for Japan in 2000. For environmental impact assessment, it has only four impact categories, but the model has a unique approach to waste. Waste generation, processing and reuse have been modelled using separate sectors and technology specific coefficients. Although the data is not very useful in most analyses since it is old and focuses on a single country, the modelling approach is worth considering, especially if one is interested in circular economy research. Another dataset with detailed waste modelling is the FORWAST dataset, integrated in SimaPro for EU and representing year 2003 data.

The EXIOBASE 2.0 (www.exiobase.eu) is a freely available update on the previous commercial EXIOBASE 1.0 database. It has data for the year 2007 for 48 regions and 163 sectors. The dataset has a large amount of impact categories, although many of them would be grouped into the same midpoint in LCIA (e.g. land use). EXIOBASE 3.0 is under development and is planned to have time series from 1995 to 2011.

14.5.2 Publicly Available Economic Accounts

In addition to specific EEIO datasets, there are some well-known datasets for economic IO. For multiple region assessments (MRIO) the Global Trade Analysis Project (GTAP) is one of the most used datasets. The current version 8 contains 129 regions and 57 sectors. The relatively coarse sector disaggregation limits analysis as does the data year (2007).

OECD maintains an input–output database, which has a harmonised set of country level input–output tables with a 58 regions and 48 sectors resolution. The database is well documented and harmonised, similar to the Eurostat database, which contains 60 sector databases for EU27 countries, candidate countries and Norway. The Eurostat datasets are updated with a three year delay, the latest dataset being for the year 2011. In addition to individual countries, the Eurostat also publishes an aggregated table for EU27. OECD also maintains an inter-country IO dataset, which has harmonised the trade flows across countries. Depending on the type of analysis, this can offer some benefits if the focus is on global supply chains. Compared to the single country dataset, the trade-flows can be used to connect several countries together into a multiple region input–output model (MRIO).

14.5.3 Adding New Environmental Extensions to Economic Input–Output Analysis

Since LCIA is progressing, many of the EEIO datasets do not contain the necessary inventory data or the characterisation models for including the relevant flows. Fortunately, it is rather straightforward to include new extensions to an IO dataset.

First the data demands of the LCIA model need to be defined. Should the input data be spatially explicit? What kind of resolution is needed? Then the country total emission and resource use amounts are gathered. In the next stage, these total amounts are disaggregated to sectors using appropriate allocation rules. The same rules as for dividing LCA processes apply here: it is usually better to use technical information to do the division, when that fails, physical and monetary allocation can be used. For example, in the case of disaggregating the EU-wide land cover classification data (CORINE) of industrial and commercial buildings a first step might be to find national statistics on industrial sites. After this, the industrial sites can be divided to the industrial sectors based on accounts on raw material extraction or material flow, and the commercial sites can be allocated to commercial sectors based on economic output. As always, it is useful to perform a sensitivity analysis to see whether the choices made in this stage influence the final outcomes of the research question (Most often not. It is the minor details, which take most of the time in disaggregation, but which provide the least benefit for the overall result).

Presented as a list, the process is the following:

1. Identify the data needs of the LCIA model (spatial resolution, resolution in regard to emission source, location and sink, most relevant emissions for the impact categories)
2. Collect statistics on total emission in the defined region
3. Use auxiliary data to disaggregate the total into sectors
4. Check the impact of choices made during disaggregation through LCIA.

A much more straightforward approach is to use emission factors or a ratio to another component already included in the EEIO dataset. For example, if black carbon emissions from combustion need to be added to the model, the energy consumption data of diesel fuel may be used, especially if additional data on the vehicle fleet of different sectors is available and can be used to justify different emission factors for different sectors (e.g. agriculture, forestry, freight road transportation, ship transportation and households). As the diesel fuel consumption is already divided by sector, the same aggregation can be used for the new emission category.

Adding new LCIA categories requires manual work, estimation and creativity. Eventually the impact category may become so critical to environmental policy, that it is integrated to the IO satellite accounts by the statistical offices. Currently this has happened mainly with energy consumption, land use and greenhouse gas emissions.

14.6 Shortcomings of EEIO

While EEIO has many benefits for LCA, it also has its shortcomings. From the viewpoint of LCA, a major flaw in most IO datasets is that they do not cover the life cycle from cradle to grave. Quite often, the end-of-life stage is missing, as is the construction of the infrastructure. These are considered as separate accounts in IO (construction investments and recycling). Some datasets (such as the CEDA 4.0) have integrated the capital investments into the input coefficients in order to give a more comprehensive picture of the overall inputs. In addition, the Japanese Waste Input–Output Table has a disaggregated waste treatment sector and the impacts of waste treatment for each sector. However, these are not common in EEIO datasets, and would have to be added through process-LCA in order to get a full cradle-to-grave assessment.

A related problem is that the IO dataset includes data for a given year. But what if the infrastructure needed has been built a long time ago and is no longer maintained? Moreover, what about the eventual demolition and recycling of the infrastructure? Although IO datasets are spatially complete, they are not temporally complete pictures of the life cycle. This is good to keep in mind, especially when comparing options that are very spread out over time. Mining and energy production systems are typical examples. Ignoring the impacts to future generations undermines the whole purpose of sustainability assessment.

As mentioned earlier, most EEIO datasets are based on a single year of production, while the emission intensities develop over time. For example, the carbon footprint of electricity production in China almost halved from 2002 to 2010 and the electricity production footprint in USA decreased by 37% (Fig. 14.5). Since the base year of EIO-LCA is 2002 and electricity generation is a major contributor to most of the carbon footprints, this means that many of the carbon footprints are now overestimated with the 2002 data. The rate of change is even more rapid in developing countries. This however is a problem which is common to both process and IO-LCA as background datasets are never up to date. A solution is to apply the path exchange method to update the emission intensities for the paths which are identified as important.

The aggregation of sectors is another problem in using the IO datasets for LCA. This can be outlined with an example. The WIOD dataset has 40 sectors and one metal product sector. We used WIOD to estimate the LCA for the underwater exploration robot in Example 14.4, where the main source of emissions was the electronics. The carbon footprint of "electronic and optical equipment" from USA was 0.28 kg CO_2-eq according to the WIOD dataset. The EORA dataset has a much more detailed classification, with 42 products listed under the category electronic

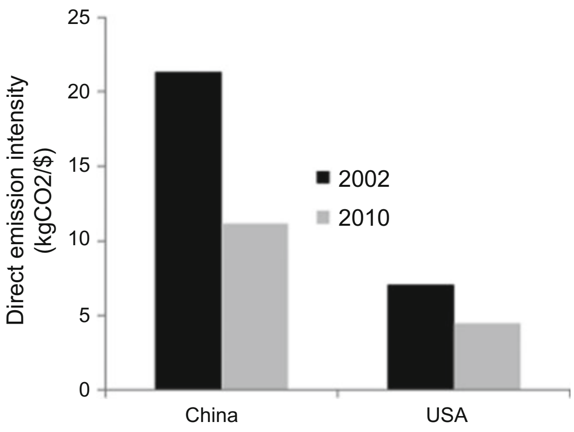


Fig. 14.5 Carbon footprint of electricity generation in China and USA in 2002 and 2010. *Source* EORA dataset factor multipliers

and measurement equipment. The carbon footprint of those products ranges from 0.38 kg CO_2-eq (electricity and signal testing) to 1.09 kg CO_2-eq (carbon and graphite products). The circuit boards and electronic components, which were most relevant for the example, would have a carbon footprint of approximately 0.58 kg CO_2-eq, which is almost twice the value obtained from the WIOD. The aggregation of expensive goods and cheaper products and components in one sector results in an underestimation of the impacts of the latter. While the aggregation has benefits in making the database easier to handle, it also results in loss of precision. The loss depends on the sector and the product, which is analysed, as well as the impact category considered. The effect is magnified, when the characterisation factors of emissions have a large spread and single substance emissions can dominate the whole result (as is the case for the toxicity-related impact categories). The more the product differs from the bulk of the sector's production, the larger the aggregation error. Fortunately, having access to a dataset like EORA means that we can double check the results from a more aggregated model against the disaggregated results, at least for the few impact categories which are included inEORA.

14.7 Summary

This chapter has outlined the application of IO in making better LCAs. The applications of IO have progressed from the research of late 1990s to applicability in case studies. The increased data availability in recent years has increased the possibilities for applying IO.

The main applications of IO in LCA are estimating inventories for flows, which are otherwise cut-off, evaluating the completeness of the LCA, highlighting potential hotspots for inventory collection and providing background data for social and economic sustainability assessment. In addition, the data sources in IO databases make it possible to evaluate the completeness and relevance of process-LCA datasets, by comparing the base year and country of the technology with the emission intensities recorded in the IO statistics.

IO-tables can be daunting at first, since they contain massive amounts of data. Once one gets used to them, they are a valuable addition to the toolbox of a LCA practitioner.

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Author Biography

Tuomas J. Mattila Has worked on LCA development since late 2000s in two fields: impact assessment and environmentally extended input-output analysis. His background is in mathematical modeling and chemical engineering. In addition to his research work he also applies ecological engineering in consultancy and farming