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Identifying data gaps in the energy supply chains of manufacturing sectors with an input–output LCA model

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ABSTRACT

National Renewable Energy Laboratory's Materials Flows through Industry tool was developed to analyze energy consumption across the supply chains of U.S. manufacturing industries. Due to the limitation of the data sources, the Tool may have incomplete data in some industries' supply chains. To overcome this issue, this study provides a method to identify data gaps in the MFI tool with the information in input–output life cycle assessment models. Results show that around 5% processes in the MFI tool have potential data gaps in the supply chain. LCA practitioners can use this information to optimize activities to improve LCA models.

1. Introduction

Developed by U.S. National Renewable Energy Laboratory (NREL), the Materials Flow through Industry (MFI) tool was designed for evaluating the energy use and other environmental impacts of the industrial production of commodity materials. The MFI tool is a cradle-to-gate linear network model. It covers a wide range of manufacturing scenarios among U.S. industries and quantifies the supply chain energy consumption, greenhouse gas (GHG) emissions and material inventories of the scenarios (Carpenter et al., 2014).

The MFI tool is similar to a process-based LCA model because they both use a bottom-up approach; however, the MFI tool also includes supply chain analyses in the US industrial and manufacturing sectors, which can capture fuel, electricity, water, and material flows within U.S. industrial sectors.

Because of the bottom-up approach, for each MFI commodity, not all of the industries in its supply chain are included, resulting in potential data gaps in its life cycle inventory. These data gaps can be identified with the assist of a top-down LCA model. Top-down LCA models refer to Input–Output LCA (IO-LCA) models, which incorporate economic relations between industrial sectors for environmental impact analyses. Compared to bottom-up LCA models, IO-LCA models have the advantage of a clearer and boarder system boundary, thus includes more accurate upstream environmental impacts in the whole supply chain.

In this research, we used this advantage of IO-LCA models to identify possible data gaps in the supply chain of process-based models. The goal was to explicitly locate data gaps in estimates of energy use associated with supply chain activity in the MFI tool commodities. These data gaps represented areas of potentially significant energy impacts that were not represented in the MFI tool. The results were also used to prioritize activity to incorporate additional data or supply chain activities to improve the existing models.

2. Methods

Both IO and MFI tool provide energy in different types of fuels, such as coal and natural gas. In this paper, we only focus on locating data gaps in total and direct energy consumption. The method we provide here can be easily applied to identify data gaps in different types of fuels. In this session, we discuss the methods we used to identify data gaps and prioritized improvement in the MFI tool. The methods have three steps: first, calculate the direct and indirect energy consumption as well as specific energy consumption in the supply chain in a given process-based tool. In this study, we use the MFI tool to demonstrate. Second, calculate same type of energy consumption in an IO-LCA model. We used 2007 US EEIO model as a case study. Third, compare the results from the IO model and the process-based model to identify data gaps. The comparison is based on energy consumption ratios. The methods

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can be applied to any process-based and IO-LCA model. Details in each step are discussed below.

2.1. MFI industry commodities energy consumption

The MFI tool provides the average fuel used to produce a commodity selected by the user. To identify data gaps for all MFI commodities, we first extracted four types of energy consumptions – total energy, process energy (include feedstock), energy for electricity generation, and energy for transportation – for each commodity from the tool. The functional units for the commodities are physical units such as kilograms and kilowatt-hour. Results showed that there were more than 400 commodities, categorized by NAICS (The North American Industry Classification System) code. Based on their NAICS code, these commodities could be categorized into agriculture (10 commodities), mining and utilities (58 commodities), and manufacturing industries (333 commodities).

2.2. I-O industry commodities energy consumption

To accurately locate potential data gaps in the MFI tool, we calculate the same four types of energy consumptions for each industry in the IO-LCA model. The total energy and direct energy consumption for each industry were calculated based on two IO-LCA basic equations (Eqs. (1) and (2)). In both equations, R and A represent the environmental matrix and technology matrix, respectively. The electricity and transportation energy use for each industry were calculated based on Eq. (3), where represents the index number of electricity or transportation sector, and represents the index number of the sector under study. The results from Eq. (3) are the sector's total electricity or transportation energy use through the whole supply chain.

$$B = R(I - A)^{-1}y \quad (1)$$

$$D = R(\mathrm{I} + \mathrm{A})y \quad (2)$$

$$B_j = R_i\left((\mathrm{I} - \mathrm{A})^{-1}y_i\right)y_j \quad (3)$$

In this study, we used the US Environmental Protection Agency's (EPA) US Environmentally Extended Input–Output (USEEIO) model's structure as the IO-LCA model (Hanes and Carpenter, 2017). The A matrix was provided by USEEIO, based on 2007 Use and Make table generated by U.S. Bureau of Economic Analysis (BEA, 2014; Yang et al., 2017). The values in the R matrix were estimated based on data from the Use table and US Energy Information Administration.

2.3. Identify data gaps in the MFI commodities

The MFI commodities were matched to IO industries based on the NACIS code of each commodity. To identify data gaps for each commodity in the MFI tool, we used the IO model's direct energy consumption, total electricity, and total transportation energy consumption as references. Conceptually, the direct energy consumption in the IO model was assumed to be the equivalent of the process fuel consumption plus the feedstock in the MFI tool. The total electricity consumption and fuel for transportation in the IO model were assumed to be equivalent to the fuel for electricity and fuel for transportation in the MFI tool.

Because the IO model uses a monetary functional unit for all sectors and the MFI tool uses functional units, a direct comparison was not possible. Converting units, in this case, would introduce large uncertainty, thus should be avoided. To make a fair comparison, we introduced a new method. The comparison was based on ratios of energy consumption shares. We used two ratios as the major indicators: (1) ratio of fuel for transportation and electricity energy to direct fuel; and (2) ratio of indirect fuel use to direct fuel use. For each commodity in the MFI tool, the result of its first indicator should be similar to the result of the corresponding industrial sector in the IO-LCA model. When comparing an MFI commodity with the corresponding IO sector, a larger ratio of transportation and electricity energy to direct fuel shows potential data gaps in the process fuel use and a smaller ratio indicates potential gaps in electricity and transportation fuel use.

Table 1
Criteria of color coding for indicators 1 and 2.

Color	Criteria
Red	1< MFI – IO
Orange	0.1 < MFI – IO < 1
White	−0.1 < MFI – IO < 0.1
Light green	−1 < MFI – IO < −0.1
Green	MFI – IO < −1

The ratio of indirect fuel use to direct fuel use was an indicator for potential data gaps in process fuel use. Because the IO model covers more supply chain energy due to the model's larger system boundary, this ratio for an MFI commodity was expected to be much smaller than the corresponding IO sector. A similar or larger value in the MFI tool indicated potential data gaps in the process fuel use. This ratio also served as an indicator to determine the significance of supply chain energy. Priorities should be given to industries that had larger process or direct energy consumption.

3. Results

We calculated the two ratios (indicator 1 and indicator 2) for each MFI commodity and its corresponding IO sector. The differences can be interpreted by 14 different scenarios (Fig. 1). The criteria for the color coding can be seen in Table 1. Detailed explanations are shown below:

- Larger MFI commodity value for indicator 1 (red or orange cell):

When an MFI commodity has a larger value of indicator 1, it shows that the fuel use for electricity or transportation for that commodity might be too large, indicating potential data gaps in the process fuel consumption.

Scenario 1 represents the situation when an MFI commodity has significantly larger values for both indicator 1 and 2. Scenarios 2–5 represent the commodities that have a significantly larger value for indicator 1, but larger or similar indicator 2. Commodities that fall in this scenario have potential data gaps in the process fuel consumption, but the gaps might not be as significate as the commodities that fall in scenario 1. Because the indirect fuel consumption for IO sectors should be naturally larger.

A larger difference (red indicator 1) shows a larger discrepancy, indicating more significate data gaps. Orange cell, on the other hand, indicates less significate data gaps. Therefore, scenarios 1–5 potentially more significant data gaps whereas scenarios 9 and 10 show insignificant data gaps. Priority should be given to scenario 1–5 when fixing the model.

- Smaller MFI commodity value for indicator 1 (light green or green cells):

A slightly smaller value for indicator 1 in the MFI tool is the result of a smaller share of electricity and/or transportation fuel compared to the IO sectors. This smaller share indicates data gaps in electricity or transportation fuel consumption. Future studies on ratios of electricity to transportation fuel use can be used to determine the exact location of the data gap.

Scenarios	Ind 1	Ind 2	Interpretation	Number of commodities	Example commodities
1	[red]	[red]	Potential significant data gap in process fuel use	13	Polyvinyl chloride
2	[red]	[orange]	Potential data gap in process fuel use	27	Silver, secondary
3	[red]		Potential data gap in process fuel use	27	Gravel
4	[red]	[light green]	Potential data gap in process fuel use	47	Argon, crude
5	[red]	[green]	Potential data gap in process fuel use	2	Basalt
6	[light green]	[light green]	Potential data gap in electricity and/or transportation fuel use	120	Cement
7	[light green]	[green]	Potential data gap in electricity and/or transportation fuel use	1	Biocides
8	[light green]	[red]	Potential data gap in supply chain fuel use	1	Cotton
9	[orange]	[light green]	Potential insignificant data gap in process fuel use	69	Soybean meal
10	[orange]		Potential insignificant data gap in process fuel use	33	Copper, primary
11	[light green]		Potential insignificant data gap in electricity and/or transportation fuel use	14	Sodium carbonate
12	[green]	[orange]	Potential insignificant data gap in supply chain fuel use	2	Electricity, diesel
13		[light green]	No Potential data gap	31	Lime
14			No Potential data gap	10	Helium

Fig. 1. Different scenarios for potential data gaps identification in the MFI tool.

- Larger MFI commodity value for indicator 2 (red or orange cells):

Indicator 2 here plays a role in identifying the significance of the data gap. When the value of indicator 2 for the MFI commodity is more than 1 times larger than the corresponding sector in the IO model, it shows that the indirect fuel consumption in the MFI is significantly larger than the IO industry. The indirect fuel consumption in the IO sectors should be naturally larger than the MFI commodities due to the model's larger system boundary. Therefore, the most reasonable explanation for a larger indicator 2 in an MFI commodity is a significant data gap in the process fuel consumption. These commodities in the MFI tool could have significant data gaps in the process fuel use and should be given priorities when updating the model.

- Smaller MFI commodity value for indicator 2 (light green or green cells):

IO sectors should naturally have larger indirect fuel consumption. When indicator 2 has a negative value, indicator 1 should be used to determine data gaps. For example, in scenario 13, though the value for indicator 2 is negative, the scenario represents no data gap situation because the value for indicator 1 is zero.

When identifying data gaps and prioritizing updates, both indicators should be considered. Using the scenarios provided in Fig. 1, we identified 13 commodities that had potential significant data gaps and should be given priority when updating the model. Most of these commodities were from the chemical product manufacturing industry. We also identified 225 commodities with potential data gaps in either process energy or supply chain energy consumption, which should be investigated following the most significant commodities. One hundred and eighteen commodities were found with potential insignificant data gaps and 41 with no potential data gaps, these processes should be given less attention when resources for updating the model is limit. In total, about 60% of the commodities have potential data gaps and the cause should be investigated.

The results found from this study were used to identify potential data gaps in the MFI tool. LCA practitioners can use this information to optimize activities to improve LCA models and assist data providers to prioritize efforts in completing inventory data.

4. Limitations

IO-LCA serves as a good reference to identify data gaps in process-based models due to its well-defined and broader system boundary and ability to capture more indirect energy consumption across the supply chain of an industry. The method introduced in this paper aims to use these advantages to identify data gaps in process-based models. However, there are some limitations when using IO-LCA as a reference. First, the comparison assumed that the IO model and results were accurate; potential uncertainties in the IO model were not considered.

Second, the comparison was based on industrial categories rather than individual products; the variance of commodities within one industrial category cannot be separated from the model. Within the same industry, commodities with different supply chains could not be differentiated. Due to these two limitations, after the potential data gaps were identified, practitioners should investigate the products individually to examine the possibility of potential data gaps by introducing other similar or different products within the same industry. Other supporting information such as other process-based LCA models and life cycle inventories should be used as references.

To address the issues above, we recommend to introduce other type of references. For example, for a number of chemical processes in the MFI tool, after the potential data gaps are identified, practitioners can use LCA databases that focuses on chemical products, to verify the data gaps. These verifications can reduce the uncertainty in the IO model; however, because most of existing LCA databases are also process-based, these models can still have boundary issues and possible data gaps in the supply chain. IO-LCA model still serves as a legitimate reference for identifying data gaps in the whole supply chain.

In addition, the IO-LCA model we used in this research is an US-based model; imports and exports were not included. This issue can be easily addressed by using multi-regional input–output model.

CRediT authorship contribution statement

Xiaoju Chen: Conceptualization, Methodology, Data curation, Writing - original draft, Writing - review & editing. **H. Scott Matthews:** Supervision, Project administration. **Rebecca Hanes:**

Resources, Software. **Alberta Carpenter:** Resources, Software, Supervision, Project administration.

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