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Introduction of a spatiotemporal Life Cycle Inventory method using a wind energy example

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Abstract

Life cycle assessment (LCA) is "primarily a steady-state-tool" and few studies to date have included dynamic temporal and spatial information in matrix-based LCA. Because of this many environmental impacts cannot be determined accurately in conventional LCA. We have integrated both temporal and spatial information in a novel dynamical life cycle inventory (LCI) framework that can produce detailed spatiotemporal results and thus offering more insights for sustainability assessment. This framework employs the existing Enhanced Structural Path Analysis (ESPA) method combined with spatial analysis to determine spatialised LCI over time. Previously we tested this new approach with a local spatial dispersion model using wheat production as an illustration. In this paper we demonstrate the new spatiotemporal LCI method over an entire life cycle, using wind energy as an example and a different approach to spatial analysis at a global scale.

Keywords: spatiotemporal; life cycle inventory; wind energy

1. Introduction

Life cycle assessment (LCA) is "primarily a steady-state-tool" that does not consider temporal or spatial information [1]. These limitations impact on results from conventional LCA and many, in particular, environmental issues cannot be determined explicitly [2,3]. In recent years more studies include either temporally or spatially explicit information, and new methodologies for temporally-explicit [2,3] and spatially-explicit LCA [4,5] have been developed. However, few studies have been performed that include both time- and space-dependent information in

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matrix-based LCA. We have integrated both, temporal and spatial information in a novel dynamical life cycle inventory (LCI) framework that can produce detailed spatiotemporal results and thereby offer more insights for sustainability assessments. This framework employs the existing Enhanced Structural Path Analysis (ESPA) method paired with spatial analysis to determine spatialised LCI over time. Previously we tested this new approach with a local spatial dispersion model using wheat production as an illustration [6]. The results show that it is possible to implement both spatial and temporal information in matrix-based LCI. However, that study only included the localised inventory at the agricultural stage of the wheat production life cycle and all upstream (e.g., fertiliser production) and downstream production (e.g., wheat transportation) processes were excluded. The aim of this paper is to demonstrate the new spatiotemporal LCI method over an entire life cycle, using wind energy as an example and a different approach to spatial analysis at a global scale.

2. Method and data

2.1. Spatiotemporal LCI

For the spatiotemporal calculation of the LCI of a system, the process structure shown in Figure 1 is used. This network diagram gives an example of how different life cycle stages (or unit processes) of a system are linked with each other and how the elementary flows of all unit processes add up to the total inventory of the final product. The lines with arrows and their thickness indicate the elemental flows between one unit process and another. To be able to use the ESPA method introduced in [6] the quantitative relationships between unit processes are represented by a technology matrix denoted by A (see Figure 1). This is an n × n matrix, where n represents the number of unit processes involved and “X” represents the amount of the processes required by one unit of the final product at Tier 1. The columns represents the tiered unit processes T1P1 (Tier 1 Process 1), . . . , TiPj involved in the life cycle of the final product. The number of columns needed for a particular tier of processes in Figure 1 is the same as the number of processes included in the network at that tier.

Then the technology matrix A is separated into several Tier-2 process matrices according to the number of Tier-2 unit processes in the network. This step is necessary to allow calculation of emissions attributable to each Tier-2 process or high-level life cycle stage of the final product. The ESPA method (as described in [6] and with more details below) is applied individually to each of the Tier-2 process matrices and the inventory result for each of these matrices is presented in an inventory map with all the locations indicated (see Figure 1).

As described in [6], applying ESPA to the LCI equation gives Equation 1, where “$*$” is the convolution of the parameters; g is the inventory vector; B is the environmental intervention matrix; and f is the final demand vector:

$$g = B * (I + A + A * A + A * A * A + \cdots) * f = B * f + B * A * f + B * A * A * f + \cdots \quad (1)$$

However, the above equation does not include information about the geographical locations of the unit processes. Therefore, another calculation step that considers the inventory per unit process at a certain location has to be added. First, A has to be extended to represent an array containing the processes and the locations of all processes. This array is called $\forall$:

$$A_{Location} = \forall_{Location} = \forall_{T1Pj}, \forall_{T2Pj}, \cdots, \forall_{TiPj}, \cdots \quad (2)$$

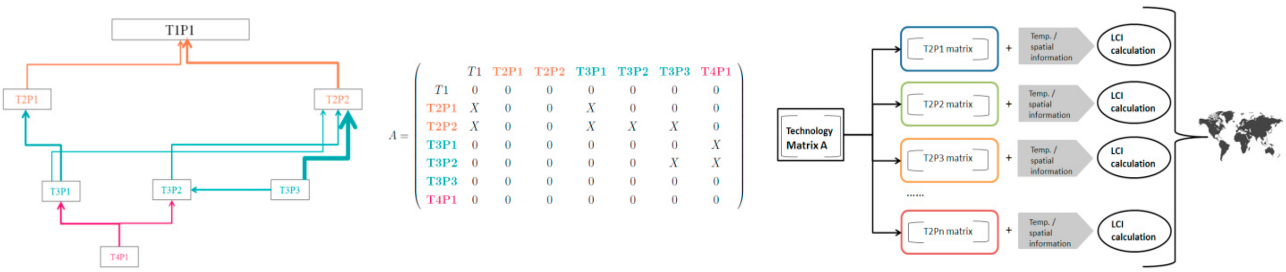


Figure 1. Example of tired network structure of a product life cycle (left) and the structure of its technology matrix A (middle) and Splitting technology matrix A into Tier-2 process matrices (right)

where, the inventory from unit processes taking place in the same region Y are saved in one temporal array. For example, in $\forall_Y = (\forall_{T1Pj}, \forall_{T2Pj}, \forall_{TiPj})$, all of the linked unit processes *T1Pj, T2Pj, ..., TiPj* take place in region Y and are therefore stored in $\forall_Y$. Applying this step to Equation 1 gives Equation 3:

$$g_{Y,l} = B * \left(I + \forall_{Y,l} + \forall_{Y,l} * \forall_{Y,l} + \forall_{Y,l} * \forall_{Y,l} * \forall_{Y,l} + \cdots\right) = B * (\forall_{Y,l} * f + \forall_{Y,l} * \forall_{Y,l} * f + \cdots) \quad (3)$$

Where, $g_{Y,l}$ is the inventory vector for a specific region Y and Tier-1 process l; and $\forall_{Y,l}$ is the technology matrix of a Tier-1 process. Calculating g for all locations involved will result in location and time specific inventory vectors. All of the inventory vectors created in Equation 4 can then be used to create spatiotemporal inventory maps.

$$g_{Y,t,l} = g_{Y,t,L}[1], g_{Y,t,L}[2], \cdots \quad (4)$$

2.2. Wind power example

Wind energy has been the subject of many LCA studies. To illustrate the new spatiotemporal LCI method developed in this study wind energy is used as an example. The objective of this example is to use the proposed method to calculate the LCI of offshore wind energy over the entire supply chain and map the inventory across space and over time. A LCI dataset was created in SimaPro based on the existing Ecoinvent datasets on UK offshore wind power generation supplemented by data on installation, operation and maintenance and decommissioning from another LCA study [7]. The dataset describes the life cycle of electricity generated from 5 MW offshore turbines off the UK coastline. As there are thousands of interlinked unit processes in the Ecoinvent database, the LCI dataset created needs to be simplified to enable fast calculation and clear demonstration of the method developed. The number of unit processes in the life cycle was reduced to 14 by removing the rest. These 14 processes represent some of the main stages involved in the life cycle of wind power and are on 4 tiers (see Figure 2).

The final product is electricity generated from offshore wind power plant and the Tier-2 processes include Component Manufacturing, Installation, Operation & Maintenance (O&M) and Decommissioning of the wind power plant. The Component Manufacturing process is linked to two Tier-3 processes manufacturing of the fixed and moving parts of the wind power plant, which are further linked to four Tier-4 processes including copper production, steel production and production of the electricity and diesel used in the Component Manufacturing processes. The Installation, O&M and Decommissioning processes are all linked to the Tier-3 process marine vessel operation, which are represented here by the Ecoinvent dataset “Transport, freight, sea, transoceanic ship”. The O&M process is also linked to another two Tier-3 process lubricant oil production and air transportation by helicopter. A 14 × 14 technology matrix A was derived from the dataset. This simplified technology matrix means that any LCI results will be much lower than those are normally expected from a reasonably complete dataset. But it should be noted that the purpose for this example is to illustrate the spatiotemporal LCI method rather than calculating an accurate LCI.

The values of the matrix entries reflect the amount of processes required by the processes at a higher tier. For each Tier-2 process (Component Manufacturing, Installation, O&M and Decommissioning) separate matrices including their linked lower-tier processes are built and used for the next calculation step (as shown in Figure 1). Using these 4 Tier-2 process matrices enables us to attribute the elementary flows, here using fossil CO_2 emission as an example in this study, to each Tier-2 process (i.e., a high-level life cycle stage of a wind power plant) instead of aggregating them for the final product (wind power) only.

A temporal dimension is added to all Tier-2 process matrices to allow the use of the ESPA method for the spatiotemporal calculation. The chosen time step is a month. The duration of the Component Manufacturing stage (including the lower-tier processes such as manufacturing of fixed and moving parts, production of copper and steel, electricity and diesel) is assumed to be 12 months. The Installation and Decommissioning stages (including the lower-tier process ship transport) are both assumed to last one month. The longest period is assumed for the O&M stage with 200 months, which gives a total of 210 months for the entire life cycle. Production of electricity, copper, steel and lubricant oil are continuous over time rather than just for use in the processes in the wind energy life cycle.

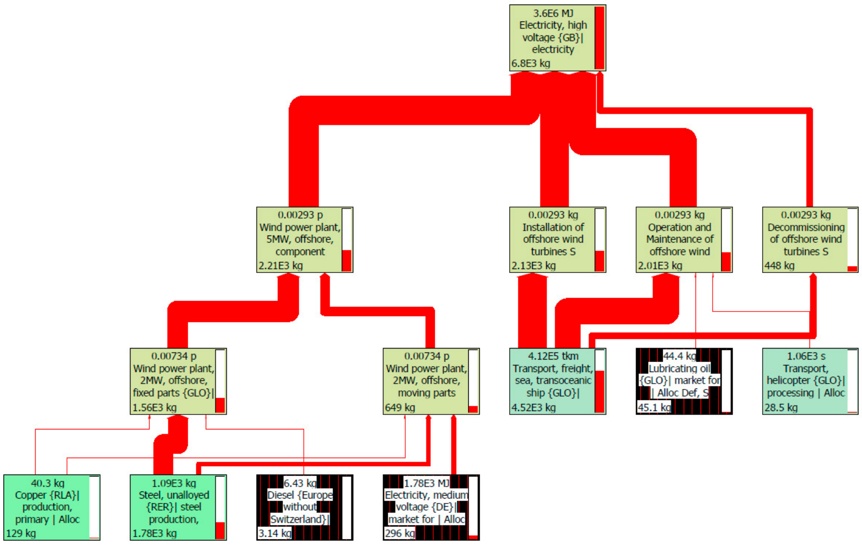


Figure 2. Process network for electricity generated from 5 MW offshore wind turbines (numbers shown are GHG emissions)

Therefore, the emissions of these processes are assumed to spread evenly over the entire duration of their respective Tie-2 processes. As explained in [6] ESPA uses temporal distributions and Figure 3 shows an example of such distributions.

The spatial scale of the processes is set at a country level in this study due to the limited spatial information available in the Ecoinvent database. For the steel production process Russia, Turkey, Ukraine and Italy have been chosen as they are the biggest steel producers in Europe. For copper production in Latin America Chile, Peru, Brazil and Bolivia have been selected due to their copper production volumes. The overall emissions per life cycle stage are apportioned among those countries according to their production volume. 75%, 15% and 10% of the emissions incurred by the Component Manufacturing stage can be attributed to the production of steel, copper and electricity, respectively. The wind power plant will be installed in UK waters and the Decommissioning stage which covers disposal and recycling of materials will also take place in the UK.

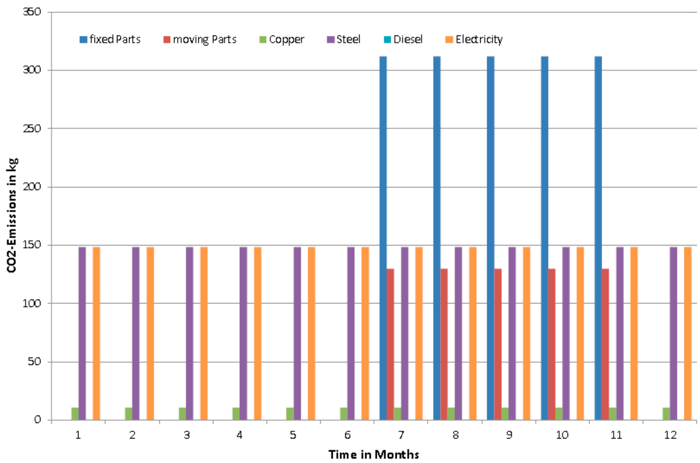


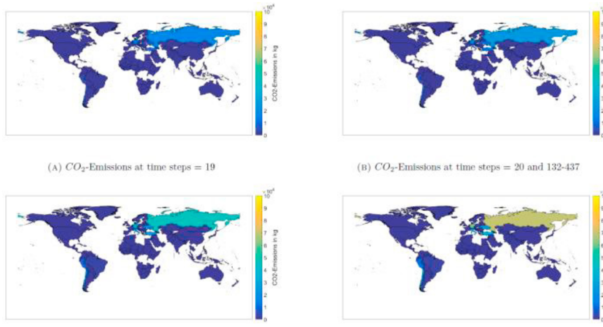
Figure 3. Temporal distributions for processes at the Component Manufacturing stage

3. Results and discussions

Figures 4-6 show the fossil CO_2 emission inventory obtained for each high-level life cycle stages of 1 GWh of electricity produced from a UK offshore wind power plant that consists of 5 MW turbines. The Component Manufacturing stage is represented in Figure 4, the stage with the highest emissions within the life cycle. It shows the emissions for the copper and steel production stage in Europe and Latin America as well as the electricity and diesel use in Germany. Emissions were summed up and displayed over 4 periods. Similar emissions during the O&M stage are presented in Figure 5. The emissions during the Installation and Decommissioning stages are presented in Figure 6. The idea for this example is not to perform an accurate LCA but to create emissions maps over time to show the temporal and spatial occurrences over an entire life cycle.

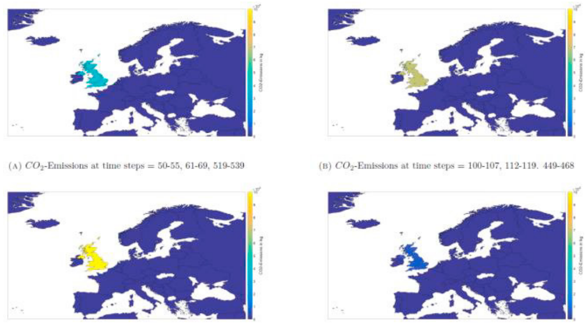
The spatiotemporal LCI method developed was tested by applying it to a simplified dataset for electricity generated from 5 MW offshore wind turbines as an explanatory case study. Using an explanatory case study and creating a simplified dataset involves making assumptions regarding process flows and about the amount of details included in the system. The Ecoinvent dataset on electricity generation from 5 MW offshore wind turbines was used as a basis to create the simplified LCI. It was intended to include a few key processes such as raw material production, transport and energy use within a wind power life cycle. As the simplified dataset has only a couple of processes that do not interact a lot with each other or loop, the convolution creates 0 entries in the matrix, resulting in only a few entries representing releases of emissions. With more interaction among processes the temporal convolution performed in ESPA would produce results greater than 0. So emissions for more time steps occur and could be shown in the maps and a wider range of emissions can be calculated. A way to avoid this is using dummy values in an explanatory example rather than trying to have realistic values in a small dataset, especially when the example is only used to show the benefits of the method. Furthermore, datasets in Ecoinvent or other LCI databases do not include temporal or spatial information in the way it would be applicable for the method. Hence, further assumptions about timing of emissions for each included process have to be made manually and being imported into the calculation. To fully automate this method datasets have to include temporal information about when and how much emissions are released by processes within the system.

The maps used in this study were created using the Matlab Mapping Toolbox. Another way to represent the spatial information is the use of GIS software rather than the Matlab Mapping Toolbox, therewith stored GIS data such as locations, countries, amount of released emissions in the area and production volume of a certain process can be used to create a layered emission map. More detailed information would also be beneficial to fully automate the proposed method. The advantage of the study performed in this paper is the connection between spatial and



(A) CO_2-Emissions at time steps = 19
(B) CO_2-Emissions at time steps = 20 and 132-437
(C) CO_2-Emissions at time steps = 21 and 38-131
(D) CO_2-Emissions at time steps = 22-37

Figure 4. CO_2 emissions during the Component Manufacturing stage



(A) CO_2-Emissions at time steps = 50-55, 61-69, 519-539
(B) CO_2-Emissions at time steps = 100-107, 112-119, 449-468
(C) CO_2-Emissions at time steps = 150-153, 160-307
(D) CO_2-Emissions at time steps = 609-618

Figure 5. CO_2 emissions during the O&M stage

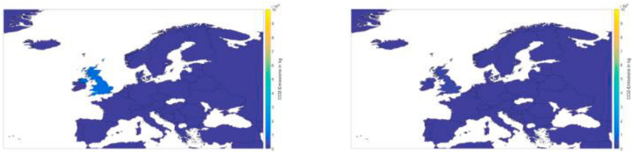


Figure 6. CO_2 emissions during the Installation (left) and Decommissioning (right) stages

temporal information to show where and when emissions during a process occur and how much transportation is needed from one location to another. With the current data available in databases the proposed method cannot be automated and many assumptions especially in terms of temporal information have to be made. An algorithm extracting the spatial information of the used datasets in Ecoinvent would have to be created and implemented into the calculation. The extracted data can then be used to create the spatial component within the life cycle matrices as so far this information has to be extracted manually. Using the same algorithm the method can be scaled up to include a higher number of processes or an original dataset from Ecoinvent and therefore, a higher resolution of processes. With more available data on the temporal distributions of processes the algorithm can be linked to define tempo-spatial processes or activities. Temporal distributions of any shape can be added to a dataset from an LCI database including its spatial information and a static value that it is given in the process or environmental matrix. However, the overall value of each of the distributions stays unchanged to the extracted value from the database. Having temporal information, e.g. in form of temporal distribution, implemented into LCI databases would further simplify the application of the method as information required for the dynamical LCI calculation could be derived at once and less assumptions regarding temporal behaviour have to be made.

4. Conclusions

This paper demonstrates a spatiotemporal LCI method using a wind energy example. The aim is to take a step back from the very localised spatiotemporal calculations performed in our previous study [6] and include entire life cycle in the LCI calculation. A simplified inventory dataset for the production of electricity from offshore wind farms was used in the illustration. The results are plotted according to their product stage and considering their temporal appearance. The method highlights the importance of spatiotemporal LCI in an era of globalisation as it helps identify more sustainable production processes over time and space to reduce environmental impacts. It can also be combined with local details such as those shown in [6] to show the inventory not only at the global scale but also very local scale. A more accurate and meaningful impact assessment can then be performed based on the LCI. Then maps showing different impacts over time and for all life cycle stages can be produced.

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