Journal of Cleaner Production 116 (2016) 198–206

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Framework and computational tool for the consideration of time dependency in Life Cycle Inventory: proof of concept

Ligia Tiruta-Barna [a], [b], [c], Yoann Pigné [d], Tomás Navarrete Gutiérrez [e], Enrico Benetto [e], *

[a] Université de Toulouse, INSA, UPS, INP, LISBP, 135 Avenue de Rangueil, F-31077 Toulouse, France
[b] INRA, UMR792, Laboratoire d'Ingénierie des Systèmes Biologiques et des Procédés, F-31400 Toulouse, France
[c] CNRS, UMR5504, F-31400 Toulouse, France
[d] LITIS, Normandy University, 25 rue Philippe Lebon CS 80540, 76058 Le Havre Cedex, France
[e] Luxembourg Institute of Science and Technology (LIST), 5, avenue des Hauts-Fourneaux, L-4362 Esch-sur-Alzette, Luxembourg

ARTICLE INFO

Article history:
Received 20 February 2015
Received in revised form
4 December 2015
Accepted 6 December 2015
Available online 13 January 2016

Keywords:
Life cycle assessment
Dynamic
Process modeling
Supply chain modeling
Graph search
Temporal

ABSTRACT

Conventional Life Cycle Inventories (LCIs) are static models of product systems without time dependent functioning of plants and time lags between supply and demand of products. The aggregation of environmental interventions without consideration of the time dimension represents an acknowledged limitation of the Life Cycle Assessment (LCA) method. In this paper we present a novel conceptual and computational framework for the consideration of time dependency in LCIs. Process modeling is used to describe the production flows and environmental interventions of each unit process and supply modeling is used to include time lags on the raw materials exchanged by unit processes of the product system. The combination of production and supply models in life cycle networks, based on a set of specific temporal parameters (representative functioning period, production time, supply delay, supply frequency), allows the characterization of time dependency in each node. For the computation of time dependent LCI, i.e. of the time resolved environmental interventions, graph search algorithm is proposed and implemented in a prototype Web application. In terms of results, the new approach provides time dependent LCI expressed as: i) time as a function of individual emission (or resource consumption) for individual processes, ii) aggregated time as a function of a given environmental intervention. A test bed case illustrating the effectiveness of the conceptual and computational approaches (proof of concept) is presented and successfully solved both analytically and numerically.

1. Introduction

1.1. Rationale

In conventional Life Cycle Inventories (LCIs), product systems are typically modeled assuming a steady state operation of unit processes and neglecting time lags between supply and demand. Average inventory data about raw materials consumptions, pollutant emissions and resources consumptions are usually collected for each unit process, and further aggregated in cumulated LCI results without providing information on the specific environmental interventions over time. However, this practice only approximates the possible range of operation of product systems in the real world. Indeed, unit processes can either show significant dynamic ranges of variation over a short time scale (e.g. in the case of biochemical processes) or can last for a long time and therefore face very different operational and environmental conditions (e.g. in the case of buildings). Time lags and the supply mode can be of great influence, e.g. in the case of reactants used in the chemical industry, which are usually supplied in batches. By considering time dependency in product system modeling, the resulting pollutant emissions and resource consumption will acquire a new dimension which is currently missing in LCIs. A further combination of Life Cycle Impact Assessment (LCIA) models, irrespective whether they are static or dynamic (e.g. using time dependent characterization factors – CFs), can therefore lead to more comprehensive and reliable LCA results.

The lack of time dimension in LCA is henceforward acknowledged as a method's limitation. A literature review of the

---

* Corresponding author.
E-mail address: enrico.benetto@list.lu (E. Benetto).

http://dx.doi.org/10.1016/j.jclepro.2015.12.049
0959-6526/

consideration of time in LCA was published by Collinge et al. (2013) and Beloin-Saint-Pierre et al. (2014).

1.2. On the notion of “temporal dependency” or “dynamics” in LCA

Published literature on the consideration of time in LCA is based on different definitions of the terms “dynamic” and “time dependency”. For example Pehnt (2006) associated the term “dynamic” to the consideration of different prospective scenarios in LCI. This approach referred only to possible modifications of LCI processes at different time horizons, because of technological changes or supply shifts. In Levasseur et al. (2010) and Kendall (2012), the notion of “time dependency” is associated to a higher level of time accuracy. The authors focused on the consideration of time dependency in LCIA of greenhouse gas emissions, by recalculating the CFs specific to emissions over the timeline of the product system lifecycle. However, these approaches are more centered on the LCIA step of LCA. Indeed, while the LCI emissions have to be placed along the time line in order to comply with the time dependent CFs, the approaches do not investigate how to combine the different dynamics of the unit processes together (and related environmental interventions) to finally calculated the resulting pollutant emissions over time. Collet et al. (2013) adopted a stepwise approach in selecting the processes deserving a temporal characterization, based on a screening of the results obtained from a given LCIA method. Consequently, the resulting characterization is dependent on the prior choice of the LCIA method, and is therefore affected by its limitations and uncertainties. Other similar seminal papers propose nuanced definitions and applications of temporal characterization, without a comprehensive discussion of an operational approach to the characterization, on the one side, and to the computation, on the other side, of time dependent LCIs. The present work tackles this endeavor, more specifically by addressing the dynamic features introduced above in Section 1.1. With this aim, we focused only on the consideration of time dependency in LCI, i.e. time dependency in LCIA is out of scope. Within this narrower scope, to the best of our knowledge, the two only papers addressing both the characterization and computation challenges are Collinge et al. (2013) and Beloin-Saint-Pierre et al. (2014). These references also present a detailed literature review on the topic of dynamic LCA, which will not be repeated here because of space constraints (the interested reader is invited to consult these papers).

1.3. Characterization of temporal dependency in LCI

By “time dependency” and “dynamic”, it is meant hereafter the comprehensive consideration (and then computation) of temporal characteristics in generic LCIs. Collinge et al. (2013) consider the following types of characteristics: i) temporal variations of the functional and reference units of industrial systems and supply chains (e.g. temporal variation of the use of a building unit, leading to different heat demands and related production technologies); ii) dynamic modeling of unit processes (i.e. different ranges of operation of unit processes); iii) temporal variations of environmental interventions (e.g. the temporal profiles of CO_2 emissions in a combustion process given the range of operation specified in ii). These characteristics are illustrated by considering *different data sets for specific time horizons* (e.g. a given year) and aggregated over a time duration (e.g. one year) in the technological (“A”) and environmental (“B”) matrixes *of the conventional LCI computational model* from Heijungs and Suh (2002). This time characterization approach marks a progress as compared to static LCIs, but it has limited use because of the coarse representation of the supply chain dynamics, and lack of a general method for determining the occurrence in time of each network's process. Beloin-Saint-Pierre et al. (2014) went one step further by considering *discrete distributions around a zero reference time* which replace the elements of technological and environmental matrixes. They clearly pointed out two additional components: iv) the calendar relative characteristic of temporal differentiation (i.e. the reference to a specific time horizon for the whole LCI) and v) the accuracy of the time scale for the temporal distributions describing the unit processes and the functional unit (i.e. the level of detail at which the process dynamics is described, e.g. daily, monthly, yearly …). The main limitation of these two seminal works is, however, the *lack of consideration of the time dependency of demand-supply relationships* between producers and consumers along the supply chain, requiring additional dynamic supply models, as it will be shown later in the present work. Despite Collinge et al. (2013) acknowledging the importance of considering these new supply models, they did not include them in their approach because of the data gaps and increase of modeling complexity. In both cases, the above cited authors assume that the practitioner is able to define the relevant temporal characteristics for each specific unit process. This is however not straightforward (hampered by the access to specific data) as it results from the combination and interactions of process and supply dynamics, further complicated by the presence of loop paths in the life cycle network of processes.

1.4. Computational challenges of temporal dependency in generic LCI

Both papers consider a mathematical model for the computation of dynamic (and generic) LCIs, using the time characterizations described above, which is a distinctive feature from the rest of the literature on dynamic LCA. The mathematical models in the two papers are rooted on the conventional matrix-based LCI computational approach from Heijungs and Suh (2002):

$$\boldsymbol{s} = \boldsymbol{A}^{-1} \times \boldsymbol{f};\ \boldsymbol{g} = \boldsymbol{B} \times \boldsymbol{s} \quad \text{and} \quad \boldsymbol{i} = \boldsymbol{C} \times \boldsymbol{g} \tag{1}$$

B is the matrix of environmental interventions (pollutant emissions and resources consumed) by each process; **A** is the technological matrix (square $m_x m$, its diagonal equals 1) describing quantitative relationships between processes and products; **f** is the functional unit vector, i.e. the outputs from the industrial supply chain required for the studied system; **s** is the scaling vector; **C** is the matrix of LCIA characterization factors, **i** is the impact results vector.

The approach was initially adapted by the same authors for spatial differentiation and then, by analogy, considered for temporal differentiation as well. A further operationalization of the approach for spatial differentiation was achieved by Mutel and Hellweg (2009). Collinge et al. (2013) basically apply the approach from Heijungs and Suh (2002) and resolve the time dependent LCI by using matrix inversion. They consider simplified time characteristics – e.g. the use of *different datasets* for different time horizons – to be used in a conventional matrix inversion, while recognizing the difficulties to operationalize such an approach due to the massive number of time characteristics involved, which furthermore are actually lacking in LCI databases.

Beloin-Saint-Pierre et al. (2014) propose an alternative approach (named ESPA) including the use of the power series expansion approach to avoid matrix inversion and the replacement of the products between the matrix elements by a product of convolution of the distribution functions. They propose to use discrete distributions as time characteristics, to be further propagated using the convolution product applied on a conventional matrix structure. The computational details and the numerical applicability of the