The International Journal of Life Cycle Assessment
https://doi.org/10.1007/s11367-017-1435-3

CONFERENCE REPORT

The integration of energy scenarios into LCA: LCM2017 Conference Workshop, Luxembourg, September 5, 2017

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Received: 30 November 2017 / Accepted: 22 December 2017

1 Foreword

The Life Cycle Management Conference, held in Luxembourg from the 3rd to the 6th of September 2017, was the opportunity for LCA practitioners to sit and discuss the integration of external models in prospective LCA models. The workshop organizers feel that as a growing LCA subdiscipline, prospective LCA lacks a shared foundation in terms of methods, data, best practices, and software solutions.

For practitioners, this workshop was organized as a first step to introduce their research, identify overlaps, pinpoint further needs, and discuss the near future of prospective LCA. The focus was placed on the use of energy scenarios in prospective LCA due to the important role of energy in the environmental profile of many products. For this reason, most of the examples are related to energy system models and energy scenarios. However, this approach is applicable to any sector likely to face changes in the future, such as transportation, agriculture, or mining.

The first half of the workshop consisted of five short presentations of current and past attempts at integrating energy scenarios into LCAs, with a highlight of the challenges encountered and how they were overcome. The workshop's second half was dedicated to discussions and organized as a breakout meeting to collect the concerns and expectations of the attendees. The challenges identified in the first half were confirmed, more emerged, and all are summed up in this document.

This report is organized into the following sections. First, a brief overview of the five introductory presentations is provided. Second, the key challenges of the integration of external models and prospective LCA that emerged from the presentations and the discussions are listed and framed within the latest literature. Thereafter, various potential solutions and research avenues identified during the discussion are detailed and further elaborated. Finally, the concluding section contains a brief discussion and last remarks.

2 Report on the presentations

Laurent Vandepaer (LIRIDE-Université de Sherbrooke, Canada, and PSI, Switzerland) gave an introduction about the interest of the integration of external models into prospective LCA. He then presented his recent work to update marginal electricity mixes in ecoinvent v.3.4 based on the compilation of public energy scenarios from 40 different countries to calculate the marginal electricity supply mixes (Vandepaer et al. 2017). Thomas Gibon (LIST, Luxembourg) presented the lessons learned about aggregation and disaggregation of datasets, life cycle inventory (LCI) modification, and technology mapping, from the development of the THEMIS framework (Gibon et al. 2015). Miguel Fernandez Astudillo (LIRIDE-Université de Sherbrooke, Canada) gave an overview of the use of TIMES models together with LCA and described the challenges of linking bottom-up models (e.g., TIMES) with process-based LCA inventories (Astudillo et al. 2017b). Didier Beloin-Saint-Pierre (Empa, Switzerland) presented his work on the integration of energy scenarios from the Swiss TIMES energy model (STEM) in the environmental assessment of the Swiss mobility sector. He summarized the challenges encountered during this project such as the use of

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Published online: 17 January 2018

temporal differentiation of LCI datasets and uncertainty issues. Brian Cox (PSI, Switzerland) gave an overview of the integration of results from the Integrated assessment model IMAGE into the ecoinvent database to create background database versions that are more representative of the future. He also introduced the "WURST", an industrial ecology Python package used to modify datasets systematically at the database level (e.g., technology markets, performance parameters, and emissions values.). The presentations are all available at https://github.com/IndEcol/wurst-examples.

3 State of the art

A large variety of models exist to make projections about future technological and environmental changes. They often rely on optimization, simulation, general equilibrium, or other macro- and micro-economics techniques. Furthermore, these techniques may even be combined together into Integrated Assessment Models (IAM), which prove appropriate in an industrial ecology context (Pauliuk et al. 2017). These modeling tools can be integrated into life cycle assessment (LCA) as data inputs, to build lifecycle inventories that are more representative of future situations. Nevertheless, the realization of a practical connection between the various models and LCA can be challenging and time-consuming. This is due to differences in the organization, structure, and technological and methodological inconsistencies between the models and LCA (Dandres et al. 2011; Gibon et al. 2015; Igos et al. 2015). In other words, practitioners should ensure that the advantages of crossing the detailed environmental modeling of LCA with robust scenario-making from other techniques introduce more benefits than it costs in terms of accuracy, time, and general relevance.

With the development of new tools from the LCA field and from other data-intensive domains, there is an opportunity to stop reinventing the wheel in every project and to create a common open framework addressing this issue. From what emerged during the workshop, the ultimate goal for prospective LCA practitioners is to build a suite of tools allowing systematic connections, following unified protocols for data integration. These instruments could then be applied to any existing or new project and consequently, provide greater transparency for data manipulation and increased traceability of data input, making prospective LCA more easily reproducible than existing attempts.

As illustrated in Fig. 1, proper prospective modeling should include the expected development of matrix coefficients, such as emissions, recycling shares, and material efficiency. This degree of consistency is desirable so that the whole range of environmental impacts can be adequately covered; e.g. reduction in emissions will lead to lower air pollution, dematerialization and recycling to lower material resource depletion, etc. (see the decomposition analysis performed in Bergesen et al. 2014). On the other hand, the more changing parameters are included, the more difficult it is to ensure consistency, and to keep track of uncertainty – both at the foreground level (i.e. the system-specific parameters, in the "Local" column of Table 1) and at the background level (i.e. the large-scale structural changes, in the "Regional or global" column of Table 1).

A tentative summary of the prospective elements that can be integrated into prospective LCA models is introduced in Table 1. The first focus of prospective LCA is the foreground system, of which the practitioner generally has the most knowledge. This is where learning curves can be applied to system-specific changes in LCI parameters, such as an increasing process efficiency or recycling rate, and lower emissions. Coefficients altering inventories

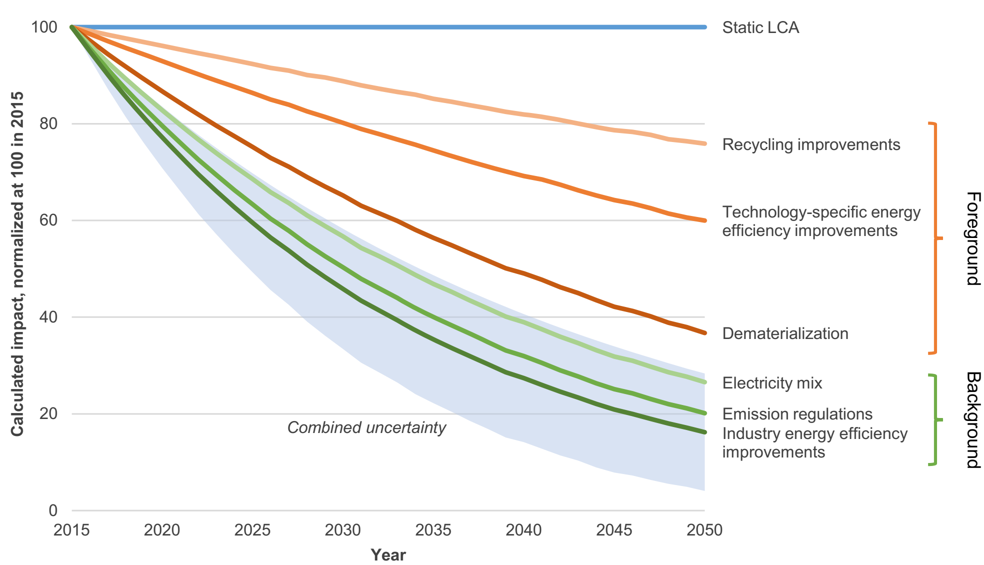

Fig. 1 Examples of parameters that can significantly influence the LCA of a system over the long term, with their potential combined uncertainty propagated

Table 1 Layers of considerations of prospective LCA. In gray, the model parameters addressed during the workshop

System scope		Geographical scope		
		Local	Regional or global	
LCI	Technosphere	System-specific changes in parameters: - energy efficiency - material efficiency - lifetime - recycling rate at the end of life, etc. "Foreground" in Fig. 1	Change of composition of market mixes electricity generation, transportation, and other non-energy sectors. General industrial trends (e.g., increase in recycling rates, improved tailing treatments, and increase material efficiency). "Background" *in* Fig. 1	Larger changes affecting the system as whole or part of it, feedback effects from upcoming environmental degradation, examples: - ore grade degradations - negative climate change effects on infrastructure - albedo change in biomass systems - rate of ocean acidification
	Biosphere	- Direct emissions due to efficiency - Material requirements	- Direct emissions due to efficiency and to regulations - Material requirements	
LCIA methods		Left unchanged	Left unchanged	Changing impact assessment data (e.g., GWP dependent on atmospheric GHG concentration)

might originate from technical documentation, technology platform publications, scientific literature, or even patents or gray literature (Gavankar et al. 2015). A second step in prospective LCA is the modification of the background data, over which a practitioner usually has a more general view. This is where energy scenario data show their main interest since they are the best available sources to modify large-scale parameters such as energy mixes, transportation markets, and general industry trends. Finally, a last *ideal* step in LCA is to completely integrate the technosphere/biosphere system, possibly with the inclusion of spatially or time-differentiated LCIA methods (Oberschelp et al. 2017; Verones et al. 2017). At this point, the most promising models are IAMs (Pehl et al. 2017; Arvesen et al. 2018), but given their complexity and resource-intensiveness, they are not addressed in this paper.

3.1 Structural inconsistencies

The technological resolution and classification of life cycle databases and prospective models rarely coincide. This causes a mismatch in terms of data structure which raises challenging technology matching problems to link one entity to the other.

Prospective modelers on the one hand, as well as LCA practitioners on the other hand, usually do not have an expert knowledge of each technology analyzed and are not always able to substantiate the matching properly. The current situation is problematic as matching technologies is generally realized manually and arbitrarily relying on name "resemblance," between the prospective model and the technologies in the LCA database, or on informed guesses (e.g., assuming coal power in India can be proxied by coal power in Poland).

Further, this matching problem can be categorized into three subgroups, where n is the number of technologies in prospective energy system models (ESM) and the LCA database:

(1) $\boldsymbol{n}_{\mathbf{ESM}} = \boldsymbol{n}_{\mathbf{LCA}}$: the cases where the technological resolution is similar.
(2) $\boldsymbol{n}_{\mathbf{ESM}} > \boldsymbol{n}_{\mathbf{LCA}}$: the detail in prospective models is higher than in the LCA database; technologies must be aggregated to match them to the technologies represented in the LCA database.
(3) $\boldsymbol{n}_{\mathbf{ESM}} < \boldsymbol{n}_{\mathbf{LCA}}$: technological and geographical details are higher in LCA database than outputs from prospective models which requires disaggregation.

The second case leads to losing some detail available in the scenario and the aggregation might be done arbitrarily.

Based on the workshop discussion, the third subgroup is the most common with energy scenarios. Results from scenarios are often made public in aggregated format grouping all technologies from a same sector or technology groups (an interesting call to the energy system model community would be to provide outputs which are more disaggregated) or they are simply coarsely-defined. Consequently, it is not always straightforward how to match technologies from aggregated prospective models to detailed LCI datasets. Practitioners might choose to disaggregate based on current market shares which can be highly time-consuming as adequate data are often missing and is misleading as they are likely to evolve over the years. As an example, the output from the European Commission reference scenario (European Commission 2016) contains a total of ten electricity production technologies, whereas the ecoinvent 3.4 database contains about 2700 activities able to produce electricity. The lack of detail from energy scenario output is therefore difficult to interpret in bottom-up, life-cycle terms, as shown in Table 2, where the "Solar," "Hydro," or "Wind" must be interpreted by the practitioner, using either third-party data or best estimates.

It is worth mentioning that a fourth case exists, in which there is not exact and direct match between any disaggregation/aggregation of one set with the other original dataset, and where both must be disaggregated in order to map a proper correspondence. This fourth case can be illustrated by an ESM dataset containing the categories "Photovoltaics, ground-mounted" and "Photovoltaics, roof-mounted" which then has to be matched with LCA processes "Polycrystalline silicon photovoltaics," "CdTe photovoltaics," and "CIGS photovoltaics," as is the case in Hertwich et al. (2015). The ESM data needs to be disaggregated into the various PV technologies, while the LCIs also have to be disaggregated into ground- and roof-mounted (or rather adapted to the different bills of materials required in these two cases).

3.2 Data inconsistencies

The objective of LCA is to inventory and characterize all flows of energy and materials, emissions, and waste that are connected directly or indirectly to a given system. For this reason, LCA requires a high level of detail in many different sectors. Tools currently used in sustainability assessment are still far from reflecting the complexities at play in the real world and can only be considered as valid for idealistic and isolated cases (Cucurachi and Suh 2017). This observation is the reason why "foreground" and "background" are usually distinguished in LCA, even though these systems are modeled in a mathematically identical way.

These limitations are also present in prospective models. Therefore, to cover the full scope of LCA, it becomes necessary to mix models and sources with various technological, sectoral, and geographical scopes (Marvuglia et al. 2013; Arvidsson et al. 2017). This comes at the price of a loss in accuracy, as prospective models are generally not designed to exchange and to connect with each other. A full coupling is very difficult, and mixing models leads to inconsistencies due to many potential differences that led to their construction (e.g., underlying assumptions, technology details and level of aggregations, in the input data and output format, and temporal scope).

Furthermore, the technological parameters used to model the technologies in the prospective models and LCA models are generally different. For example, in the case of energy production, one might represent gas power plant with an efficiency of 55% and a lifetime of 20 years while the other uses a value of 66% and 25 years. For increased consistency, it is important to harmonize the technological information

Table 2 A possible matching for the electricity production technologies of the European Commission 2016 baseline scenario (PRIMES model) and ecoinvent 3.4

European Commission 2016	ecoinvent 3.4, electricity production
Nuclear energy	Nuclear, pressure water reactor
Solids	Hard coal
	Lignite
Oil (including refinery gas)	Oil
Gas (including derived gases)	Natural gas, combined cycle power plant
Biomass-waste	Heat and power co-generation, wood chips, 6667 kW, state-of-the-art 2014
Hydro	Hydro, reservoir, alpine region
	Hydro, reservoir, non-alpine region
	Hydro, reservoir, tropical region
	Hydro, run-of-river
Wind	Wind, > 3 MW turbine, onshore
	Wind, 1–3 MW turbine, offshore
Solar	Photovoltaic, 3 kWp slanted-roof installation, multi-Si, panel, mounted
	CSP solar tower
	CSP parabolic trough
Geothermal and other renewables	Deep geothermal
Other fuels (hydrogen, methanol)	Not matched

contained in the LCA model and in the prospective models. Prospective LCA should learn from harmonization projects, such as the meta-analysis carried out by the National Renewable Energy Laboratory (Heath and Mann 2012). One should also consider that these may vary according to the underlying scenarios and in time. In all cases, full transparency in assumptions made is a key.

Moreover, some blocks of prospective LCA models do not have dedicated projections. Energy conversion and energy-intensive industry or transportation processes are generally the focus of prospective LCA, whereas other sectors (even with high GHG emissions associated, such as agriculture) are more often left static. In the presence of these inevitable data gaps, current situations are often used as a proxy for future situations implying temporal mismatches.

Finally, technologies unavailable at a commercial scale are usually not represented in current LCI databases but make their appearance in scenarios (e.g., carbon dioxide capture and storage, a central technology in the most aggressive climate change mitigation scenarios). A common case is also that some LCA datasets are not available for certain countries while they might appear in future scenarios (e.g., power from natural gas in Switzerland).

3.3 Addressing uncertainty

Workshop participants acknowledged that uncertainty is very rarely addressed in prospective LCA; at best, only variability is. More generally, it is challenging to assess the quality of prospective data. Addressing uncertainty, both aleatoric (or ontic, e.g., does my data include uncertainty data due to variability?) and epistemic (e.g., which emerging technologies will penetrate the market in the long-term?) require the characterization of all flows of the LCA-scenario system, from material flow coefficients to inventory parameters, to market shares. Compounding model (data-based) and scenario (method-based) uncertainties need appropriate quantification methods. Characterizing uncertainty when possible, but also quantifying and limiting it by including stakeholders in the data collection process are possible options (Wender et al. 2014). It should be noted, however, that the use of energy models is expected to improve data representativeness and precision of LCIs, reducing the epistemic uncertainty of prospective scenarios (Astudillo et al. 2017a).

3.4 Evolution of the biosphere and of the impacts

The effects of future environmental degradations on the future technosphere (e.g., change in solar Direct Normal Irradiance and change in heat demand due to climate change) or on the future biosphere (e.g., change in crop productivity due to modified weather pattern, increased ore grade degradations) are not considered in existing prospective LCAs.

Similarly, LCIA methods are not always valid for actions or impacts occurring in the future. For example, indicators with a time horizon should be adapted to address changing impact pathways. Be they average or marginal, characterization factors change along with the reference state from which they are derived. Moreover, this reference state is changing both at the midpoint (e.g., atmospheric concentration of greenhouse gases for global warming potential, ore grades for resource depletion potential) and endpoint (e.g., disability weights of DALYs for human health damage, species densities for ecosystem damage) levels. The reference state evolves in correlation with human activities, so life cycle impact assessment should also be based on dynamic properties. Finally, in a similar manner, when weighting is used, the weight attributed to different impacts might evolve over time. As technosphere and biosphere intertwine at a large scale and in the long term, the whole LCI-LCIA prospective system ought to become dynamic to represent impacts adequately. Substantial efforts have been made towards the regionalization of impact characterization (Verones et al. 2016) as well as their temporalization (Levasseur et al. 2010; Mutel et al. 2012; Tiruta-Barna et al. 2015; Beloin-Saint-Pierre et al. 2016). Yet again, facilitating the inclusion of these refined models into LCA software remains the next challenge.

4 Best practices, potential standards, and solutions

4.1 Model selection

A large variety of prospective models exist, and picking the most adequate for a specific study is challenging.

For example, in different studies, economic models are used, but it is questionable whether they always correspond to an accurate representation of the future. Several challenges are identified in the literature concerning economic models. Zamagni (2013) in her review listed the following points of attention: insufficient integration of future technologies, lack of transparency, and difficulty to evaluate uncertainty. In another study by Marvuglia et al. (2013), the complexity to feed economic models with sufficient data and the challenge to capture non-economic elements linked with human behaviors, habits, cultural heritages, regulatory constraints, and the like is emphasized. Furthermore, these models are often criticized because they rely on idealistic assumptions such as perfect competition and the idea that consumers behave in a rational and cost-optimal way (Menten et al. 2015; Wikipedia 2016; Yang and Heijungs 2017).[1] Finally, in the case of energy system, long-term models such as TIMES generally adopt a time resolution which is too low to capture the fine behavior of renewable electricity production (Krakowski et al. 2016).

Predicting the future with perfect accuracy is impossible and all prospective models have limitations. Nevertheless, these instruments are essential to think systematically about the future, to structure discussions, and provide a context to support strategic decisions (Poganietz 2017). The choice of the model must come with a transparent report of its limitations and of the assumptions that are behind it. Therefore, models allowing third-party verification should be prioritized (Astudillo et al. 2017b).

4.2 Data sharing

A *short-term* need emerging from the breakout meeting was the creation of a repository with LCI datasets of emerging, new, and future technologies. The ecoinvent database has been offering more and more inventory datasets for emerging technologies, but do not contain any data on major GHG-mitigating technologies such as carbon dioxide capture and storage. Without necessarily reaching the degree of quality required to feed the ecoinvent databases,[2] such inventories

[1] The field of economics as a whole is undergoing profound changes in the way it models how individuals make economic decisions in real life, with the emergence of "behavioral economics" – recently in the spotlight after Richard H. Thaler was awarded the 2017 Nobel Prize of Economics.

[2] For an overview of the data submission requirements, see the check list for ecoinvent data providers: http://www.ecoinvent.org/files/check_list_20170215.pdf

could be shared among prospective LCA practitioners via a shared repository. In a similar vein, a common repository for metadata on matching activity and product names for various data sources: energy (IEA, WEC, MESSAGE, energy plan, TIMES flavors), copper, building materials, future emissions of energy production technologies (IMAGE), and ecoinvent, EXIOBASE. This repository could be used to store a "translation" (or "mapping," "correspondence") table from every model to an existing LCA database, relevant sources to substantiate aggregation or disaggregation methods across the various models, uncertainty values conveying the loss of representativeness due to the mapping, and lists of parameters and assumptions that are necessary to document for the harmonization of the models.

In the medium-term, this first sharing and capitalization step should lead towards the definition of a standard for mapping prospective models' outputs to inputs of LCA models. This could look as a general strategy, an ontology, a protocol, or several updatable mapping files explaining how to deal with aggregation, disaggregation, missing information, etc., that would lift this process from a current ad hoc to a more systematic approach. Practical information such as default technologies or region proxies to use whenever you do not have enough detail in scenario data. The following pseudocode illustrates how protocol and recommendations could look like for regional matching:

(1) load a technology-region-year data point from energy scenario
(2) **SEARCH** a match for region in LCA database
(3) **IF** match exists
(4) **THEN** replace value in database
(5) **ELSE** move up one regional level (e.g., DE – > RER – > GLO) **GOTO** 2

Furthermore, the common repository would contain examples of methods to include non-LCA data to transform LCI databases. The Python module Wurst (https://github.com/IndEcol/wurst) is an example of such a method, but other prospective or non-prospective works have dealt with similar issues (Oberschelp et al. 2017).

In the longer-term, open source tools to build LCI inventories (including uncertainty) would be stored and maintained on that repository. Protocols to share, review, and reproduce product system models will be needed (Kuczenski et al., in preparation).

4.3 Software

There is a unanimous need for software that can modify LCI database on-the-fly, based on various external models and the different scenarios that they contain. The tools used to perform this type of tasks must be flexible and allow to program data manipulation requests. Open-source programming platform are a good option as they enhance transparency and reproducibility (Pauliuk et al. 2015). Moreover, they favor improvements by other users by giving them the opportunity to build easily on existing efforts.

Brightway2 (https://brightwaylca.org/) is a flexible open-source Python-based LCA framework that can be used to integrate external, prospective, and non-prospective models into LCA. Several successful integrations have already been realized in the transport and the energy sector. The Python package "Wurst" (https://github.com/IndEcol/wurst) using Brightway2 as the data backend allows the modification of datasets at the database level based, accounting for the evolution of the technologies over time. Once coupled with energy scenario data or other prospective scenarios, the module can modify technology shares in markets such as energy supply markets, key parameters in energy production sources (e.g., efficiency), emissions, and disaggregate global datasets into separate regions.

OpenLCA, an open source software is also a possible candidate. It was used in Sacchi (2017) to integrate trade data from the cement and the banana industries to modify the ecoinvent database. This work is well-documented and could be replicable for the integration of prospective models.

An example of a first step towards the streamlining of energy scenario integration in LCA discussed during the workshop is a routine able to connect mainstream energy scenarios (e.g., IEA, European Commission reference scenario, Energy Information Administration) to LCA databases in a systematic fashion. This routine could be written for a shared repository of prospective average electricity supply mixes from 40 countries for 2020, 2030, 2040, and 2050, converted and stored as LCA-friendly data for various scenarios.

5 Conclusions

Traditionally, LCA has always been a multidisciplinary practice, where chemical engineers, toxicologists, climate scientists, or ecologists have contributed substantially. Today, there is a great opportunity to enrich prospective LCA by continuously integrating, even more, disciplines, such as scenario modeling and macroeconomics. This requires a shared effort from prospective LCA practitioners to build a strong foundation on which this promising field can strive. Shared standards, common open-source tools, high traceability of the data sources, harmonization and consistency between the models, transparency in the data manipulation steps, and uncertainty quantification are key elements that were raised during the workshop. Other initiatives in the LCA world about inventory manipulations and data sharing should also be connected to this work. Finally, and at the risk of being repetitive, this effort is highly multidisciplinary and builds on models from other fields; it is therefore essential that experts and stakeholders from *outside* the LCA community be also fully involved in this endeavor.

Acknowledgements The authors thank the organizers of the LCM2017 conference, specifically Enrico Benetto and Mélanie Guiton, for the support in arranging the workshop. We also extend our thanks to Chris Mutel for constructive comments on an early version of the text.

Funding information Laurent Vandepaer is grateful for the financial support of the Laboratory for Energy Systems Analysis at the Paul Scherrer Institut (PSI), of Wallonie-Bruxelles International (WBI) through the WBI-World Excellence Scholarship, and of the Natural Sciences and Engineering Research Council of Canada through the Discovery Grants Program. This research was supported by the Swiss Competence Centers for Energy Research (SCCER) "Heat and Electricity Storage" (HaE) and "Supply of Electricity" (SoE), funded by the Commission for Technology and Innovation (CTI).

References

Arvesen A, Luderer G, Pehl M, Bodirsky BL, Hertwich EG (2018) Deriving life cycle assessment coefficients for application in integrated assessment modelling. Environ Model Softw 99:111–125. https://doi.org/10.1016/j.envsoft.2017.09.010

Arvidsson R, Tillman A-M, Sandén BA et al (2017) Environmental assessment of emerging. Recommendations for Prospective LCA. J Ind Ecol, Technologies. https://doi.org/10.1111/jiec.12690

Astudillo MF, Treyer K, Bauer C, Pineau PO, Amor MB (2017a) Life cycle inventories of electricity supply through the lens of data quality: exploring challenges and opportunities. Int J Life Cycle Assess 22(3):374–386. https://doi.org/10.1007/s11367-016-1163-0

Astudillo MF, Vaillancourt K, Pineau P-O, Amor B (2017b) Integrating energy system models in life cycle management. In: Benetto E, Gericke K (eds) Designing sustainable technologies, products and policies: from science to innovation. Springer, Luxembourg

Beloin-Saint-Pierre D, Levasseur A, Margni M, Blanc I (2016) Implementing a dynamic life cycle assessment methodology with a case study on domestic hot water production. J Ind Ecol 21:1128–1138

Bergesen JD, Heath GA, Gibon T, Suh S (2014) Thin-film photovoltaic power generation offers decreasing greenhouse gas emissions and increasing environmental co-benefits in the long term. Environ Sci Technol 48(16):9834–9843. https://doi.org/10.1021/es405539z

Cucurachi S, Suh S (2017) Cause-effect analysis for sustainable development policy. Environ Rev 25(3):358–379. https://doi.org/10.1139/er-2016-0109

Dandres T, Gaudreault C, Tirado-Seco P, Samson R (2011) Assessing non-marginal variations with consequential LCA: application to European energy sector. Renew Sust Energ Rev 15(6):3121–3132. https://doi.org/10.1016/j.rser.2011.04.004

European Commission (2016) EU reference. Scenario 2016

Gavankar S, Suh S, Keller AA (2015) The role of scale and technology maturity in life cycle assessment of emerging technologies: a case study on carbon nanotubes. J Ind Ecol 19(1):51–60. https://doi.org/10.1111/jiec.12175

Gibon T, Wood R, Arvesen A, Bergesen JD, Suh S, Hertwich EG (2015) A methodology for integrated, multiregional life cycle assessment scenarios under large-scale technological change. Environ Sci Technol 49(18):11218–11226. https://doi.org/10.1021/acs.est.5b01558

Heath GA, Mann MK (2012) Background and reflections on the life cycle assessment harmonization project. J Ind Ecol 16:S8–S11. https://doi.org/10.1111/j.1530-9290.2012.00478.x

Hertwich EG, Gibon T, Bouman EA, Arvesen A, Suh S, Heath GA, Bergesen JD, Ramirez A, Vega MI, Shi L (2015) Integrated life-cycle assessment of electricity-supply scenarios confirms global environmental benefit of low-carbon technologies. Proc Natl Acad Sci U S A 112(20):6277–6282. https://doi.org/10.1073/pnas.1312753111

Igos E, Rugani B, Rege S, Benetto E, Drouet L, Zachary DS (2015) Combination of equilibrium models and hybrid life cycle-input–output analysis to predict the environmental impacts of energy policy scenarios. Appl Energy 145:234–245. https://doi.org/10.1016/j.apenergy.2015.02.007

Krakowski V, Assoumou E, Mazauric V, Maïzi N (2016) Feasible path toward 40-100% renewable energy shares for power supply in France by 2050: a prospective analysis. Appl Energy 171:501–522. https://doi.org/10.1016/j.apenergy.2016.03.094

Kuczenski B, Marvuglia A, Ingwersen WW, et al Product system model description and revision. in Prep

Levasseur A, Lesage P, Margni M, Deschênes L, Samson R (2010) Considering time in LCA: dynamic LCA and its application to global warming impact assessments. Environ Sci Technol 44(8):3169–3174. https://doi.org/10.1021/es9030003

Marvuglia A, Benetto E, Rege S, Jury C (2013) Modelling approaches for consequential life-cycle assessment (C-LCA) of bioenergy: critical review and proposed framework for biogas production. Renew Sust Energ Rev 25:768–781. https://doi.org/10.1016/j.rser.2013.04.031

Menten F, Tchung-Ming S, Lorne D, Bouvart F (2015) Lessons from the use of a long-term energy model for consequential life cycle assessment: the BTL case. Renew Sust Energ Rev 43:942–960. https://doi.org/10.1016/j.rser.2014.11.072

Mutel CL, Pfister S, Hellweg S (2012) GIS-based regionalized life cycle assessment: how big is small enough? Methodology and case study of electricity generation. Environ Sci Technol 46(2):1096–1103. https://doi.org/10.1021/es203117z

Oberschelp C, Pfister S, Hellweg S (2017) Reduction of site-specific electricity generation particulate matter impacts in China. In: Life Cycle Management Conference 2017. Luxembourg

Pauliuk S, Arvesen A, Stadler K, Hertwich EG (2017) Industrial ecology in integrated assessment models. Nat Clim Chang 7(1):13–20. https://doi.org/10.1038/nclimate3148

Pauliuk S, Majeau-Bettez G, Mutel CL, Steubing B, Stadler K (2015) Lifting industrial ecology modeling to a new level of quality and transparency: a call for more transparent publications and a collaborative open source software framework. J Ind Ecol 19(6):937–949. https://doi.org/10.1111/jiec.12316

Pehl M, Arvesen A, Humpenöder F, Popp A, Hertwich EG, Luderer G (2017) Understanding future emissions from low-carbon power systems by integration of life-cycle assessment and integrated energy modelling. Nat Energy 2(12):939–945. https://doi.org/10.1038/s41560-017-0032-9

Poganietz W-R (2017) Predicting energy futures? Scenarios and their assessment. In: Winter School on Energy Scenarios. Kurhaus Trifels

Sacchi R (2017) LCI methodology and databases. A trade-based method for modelling supply markets in consequential LCA exemplified with Portland cement and bananas. Int J Life Cycle Assess. https://doi.org/10.1007/s11367-017-1423-7

Tiruta-Barna L, Pigné Y, Navarrete Gutiérrez T, Benetto E (2015) Framework and computational tool for the consideration of time dependency in life cycle inventory: proof of concept. J Clean Prod 116:198–206

Vandepaer L, Treyer K, Mutel CL et al (2017) Marginal electricity supply mixes and their integration in version 3.4 of the ecoinvent database: results and sensitivity to key parameters. doi:https://doi.org/10.13140/RG.2.2.14750.64324

Verones F, Bare J, Bulle C, Frischknecht R, Hauschild M, Hellweg S, Henderson A, Jolliet O, Laurent A, Liao X, Lindner JP, Maia de Souza D, Michelsen O, Patouillard L, Pfister S, Posthuma L, Prado V, Ridoutt B, Rosenbaum RK, Sala S, Ugaya C, Vieira M, Fantke P (2017) LCIA framework and cross-cutting issues guidance within the UNEP-SETAC life cycle initiative. J Clean Prod 161:957–967. https://doi.org/10.1016/j.jclepro.2017.05.206

Verones F, Hellweg S, Azevedo LB et al (2016) LC-impact version 0.5: a spatially differentiated life cycle impact assessment approach

Wender BA, Foley RW, Prado-Lopez V, Ravikumar D, Eisenberg DA, Hottle TA, Sadowski J, Flanagan WP, Fisher A, Laurin L, Bates ME, Linkov I, Seager TP, Fraser MP, Guston DH (2014) Illustrating anticipatory life cycle assessment for emerging photovoltaic technologies. Environ Sci Technol 48(18):10531–10538. https://doi.org/10.1021/es5016923

Wikipedia (2016) Perfect competition. **Wikipedia**

Yang Y, Heijungs R (2017) On the use of different models for consequential life cycle assessment. Int J Life Cycle Assess. https://doi.org/10.1007/s11367-017-1337-4

Zamagni A (2013) Identification of the affected processes: challenges and open questions. In: Blanc I (ed) EcoSD annual workshop-consequential LCA **Mines ParisTech**