Environmental Assessment of Emerging Technologies: Recommendations for Prospective LCA

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Environmental Assessment of Emerging Technologies

Recommendations for Prospective LCA

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Summary

The challenge of assessing emerging technologies with life cycle assessment (LCA) has been increasingly discussed in the LCA field. In this article, we propose a definition of prospective LCA: An LCA is prospective when the (emerging) technology studied is in an early phase of development (e.g., small-scale production), but the technology is modeled at a future, more-developed phase (e.g., large-scale production). Methodological choices in prospective LCA must be adapted to reflect this goal of assessing environmental impacts of emerging technologies, which deviates from the typical goals of conventional LCA studies. The aim of the article is to provide a number of recommendations for how to conduct such prospective assessments in a relevant manner. The recommendations are based on a detailed review of selected prospective LCA case studies, mainly from the areas of nanomaterials, biomaterials, and energy technologies. We find that it is important to include technology alternatives that are relevant for the future in prospective LCA studies. Predictive scenarios and scenario ranges are two general approaches to prospective inventory modeling of both foreground and background systems. Many different data sources are available for prospective modeling of the foreground system: scientific articles; patents; expert interviews; unpublished experimental data; and process modeling. However, we caution against temporal mismatches between foreground and background systems, and recommend that foreground and background system impacts be reported separately in order to increase the usefulness of the results in other prospective studies.

Introduction

Most life cycle assessment (LCA) studies have some kind of future-oriented feature. For example, LCA can be used to investigate how to best improve the environmental performance of an existing product in the near future. But there are LCA studies that have a clearer future-oriented scope, since they study technologies at an early stage of development. Such technologies may not have reached the market yet or have merely been introduced into minor niche markets. Some may even exist only in experimental settings, such as laboratory-scale production or as prototypes. In this article, such future-oriented LCA studies of emerging technologies are referred to as prospective LCA studies. We here propose a formal definition of prospective LCA in order to facilitate further discussions. Furthermore, the aim of this article is to discuss and analyze three
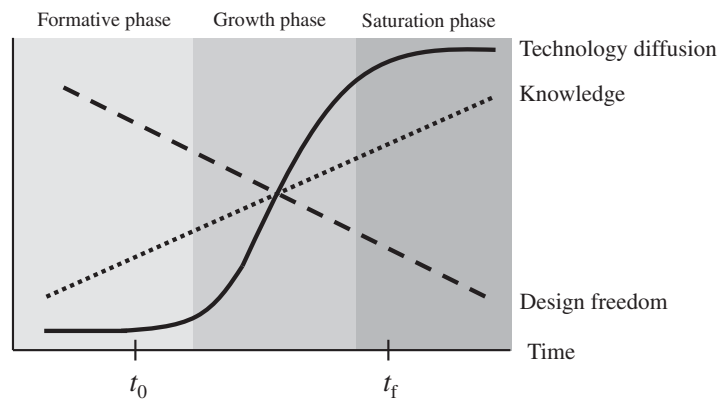
Figure 1 Schematic illustration of the technology diffusion, knowledge, and design freedom curves. In order for an LCA to be prospective, the technology should be in the formative phase or early growth phase at the current time of the assessment (t_0) and should be modeled at a future time (t_f) in the saturation phase or late in the growth phase. LCA = life cycle assessment.

methodological aspects of particular importance for the goal, scope, and inventory modelling in prospective LCA: choice of technology alternatives; modeling of foreground systems (including production scale); and modeling of background systems. This aim will be fulfilled by drawing on experiences from conducted LCA case studies of emerging technologies. The sections of this article will be structured around these aspects, followed by a concluding section with recommendations.

A number of previous studies have discussed different aspects of prospective LCA, sometimes under different names. They typically depart from the design paradox, which can also be referred to as the Collingridge dilemma after Collingridge (1980). This dilemma says that at an early stage of technological development, the possibility to alter and control is high (i.e., there are many degrees of freedom in the development), but the knowledge about the technology is sparse. At a later stage of development, more knowledge exists, but the possibility to alter the technology is reduced (i.e., most design parameters have been locked). This means that an LCA conducted at an early stage can have a larger influence on technology development. As discussed by Sandin and colleagues (2014), prospective LCA can play important roles in early research and development by providing environmental guidance, and by supporting scale-up. However, it also means that data scarcity challenges, which exist in conventional LCA as well, are exacerbated in prospective LCA (Hetherington et al. 2014). When first mentioned, the term prospective LCA was used to denote what is presently referred to as consequential LCA (Tillman 2000). It has since been clarified that both consequential and attributional studies can be prospective or retrospective (Sandén and Karlström 2007; Hillman and Sandén 2008; Herrmann et al. 2014). Prospective LCA deals with technologies in the future, whereas retrospective studies deal with products in the past, regardless of other modeling approaches. An early use of the specific term prospective LCA in the title of an article was by Spielmann and colleagues (2005), who conducted an LCA on transport systems using scenario modeling. The term has since then also been used in the titles of LCA case studies of

emerging technologies such as antibacterial T-shirts (Walser et al. 2011; Manda et al. 2015), membrane filtration systems for drinking water (Manda et al. 2014), production of the nanomaterial graphene (Arvidsson et al. 2014), and electric vehicles (Zimmermann et al. 2015).

It should be noted that the discussion about attributional versus consequential LCA is not the topic of this article, but has recently been discussed to great extent elsewhere (Zamagni et al. 2012; Brandão et al. 2014; Dale and Kim 2014; Plevin et al. 2014; Suh and Yang 2014). The examples and discussions in this article, however, refer to prospective attributional LCA.

Method and Materials

Definition of Prospective Life Cycle Assessment

What sets prospective LCA apart from conventional LCA? Consider an LCA study with the product and its system modeled at time t_m. In conventional LCA studies of existing products, and when the next product generation is compared to the current version, the situation is typically that $t_m \approx t_0$, where t_0 stands for the current time at which the assessment is conducted. The term prospective LCA, as used in this article, refers to studies of emerging technologies in early development stages, when there are still opportunities to use environmental guidance for major alterations. In order to capture the potential future environmental impacts of a technology in such cases, the system modeled is placed in a more distant future t_f in prospective LCA studies, so that $t_m \approx t_f$.

Adoption of technologies typically follows a technology diffusion curve, starting in a formative phase, continuing into a growth phase, and ending in a saturation phase (Grübler 1998; Jacobsson and Bergek 2004; Abernathy and Utterback 1978). The above-mentioned Collingridge dilemma is related to technical diffusion. Technological maturity, and hence knowledge about the technology, increases with diffusion, while the degrees of freedom decrease. These three curves are shown in figure 1, representing: technology diffusion, knowledge about

the technology, and design freedom. In order to provide relevant guidance at an early stage when alterations are still possible, t_0 should be in the formative phase or early in the growth phase. Contrarily, it is of interest to model the technology in the saturation phase or late in the growth phase, since it is at this time the technology's full environmental performance is realized. A typical example of a prospective LCA study setup would be an early- or laboratory-stage technology envisioned at a future point of mass production and use. Prospective LCA thus deals with more radical technological change that occurs over longer time frames, rather than incremental changes close in time.

Related to the technology diffusion curve in figure 1 are the concepts of technology readiness level (TRL) (US DOD 2011; EC 2014) and manufacturing readiness level (MRL) (US DOD 2015). The TRL scale indicates how far the technology has evolved in the formative phase and ends when the technology has been demonstrated in real applications. Since TRL regards only the formative phase, the technology studied in a prospective LCA can be at different TRL at t_0. However, the technology is modeled as having the highest TRL, since real applications must have been demonstrated for a technology to enter the growth phase. For MRL, low values indicate laboratory-scale production (i.e., formative phase) and higher values indicate mass production (i.e., growth or saturation phase). The technology is thus modeled as having the highest MRL in prospective LCA studies, but must have a lower MRL at t_0.

Case-Study Approach and Selection

Experience from conducted case studies is valuable for method development in LCA since it provides proof of concept and reveals need for adjustment (Baumann and Tillman 2004). Since there has been no established terminology for prospective LCA before, it is difficult to conduct a systematic literature review to identify case studies. We have instead chosen to do an in-depth reading of a nonexhaustive number of prospective attributional LCA case studies that have considered relevant methodological aspects and qualify to the definition provided in the *Definition of Prospective Life Cycle Assessment* section. The case studies are mainly from the fields of nanomaterials, biomaterials, and energy technologies (table 1).

Results and Discussion

Technology Alternatives

In conventional LCA studies, when the technology is modeled at a current stage ($t_m \approx t_0$), technology alternatives that currently exist are typically chosen for the study. Such existing technologies can be directly observed and their relevance is easy to motivate. In prospective LCA studies of emerging technologies modeled in a more distant future ($t_m \approx t_f$), it is more uncertain which technologies are relevant to study. One potential problem is that the imagination of the analyst is bound by knowledge about the current situation, leading to the

Table I Prospective LCA case studies reviewed

Case study	Emerging technology studied
Arvidsson et al. (2014)	Graphene production
Arvidsson et al. (2015)	Nanocellulose production
Bergesen and Suh (2016)	Cadmium telluride photovoltaics
Caduff et al. (2012)	Large wind power turbines
Delgado-Aguilar et al. (2015)	Nanocellulose-enforced paper
Edwards et al. (2014)[a]	Automotive fuels
Gavankar et al. (2014)	Carbon nanotubes
Gibon et al. (2015)	Concentrating solar power
Healy et al. (2008)	Carbon nanotube production
Janssen et al. (2014)	High-gravity ethanol production from wheat straw
Janssen et al. (2016)	High-gravity ethanol production from wood chips
Kushnir and Sandén (2008)	Fullerene and carbon nanotube production
Li et al. (2013)	Nanocellulose production
Liptow et al. (2015)	Ethylene production from wood
Manda et al. (2014)	Membrane filtration system for drinking water
Manda et al. (2015)	Nanosilver T-shirt
Nordelöf et al. (2014)[a]	Electric vehicles
Pini et al. (2017)	Self-cleaning float glass
Pizza et al. (2014)	Graphene nanocomposites
Roes and Patel (2011)	Caprolactam production
Shen et al. (2012)	Plastic materials
Walser et al. (2011)	Nanosilver T-shirt
Yao et al. (2015)	Ethylene production
Zimmermann et al. (2015)	Electric vehicles

[a]Review of case studies.
LCA = life cycle assessment.

selection of only alternatives that seem plausible at the time t_0. The analyst may then miss out on alternatives that are more relevant at a future time t_f. For example, Ljunggren Söderman and colleagues (2014) describe how early assessments of electric vehicles in the 1990s assumed lead acid batteries in the modeling. Today, they write, few would consider the lead acid battery electric vehicle to be a good proxy for the electric vehicles currently used and under development (which rather use

lithium ion batteries). This example illustrates the importance of going beyond current state-of-the-art technologies at t_0 in prospective LCA and also include alternatives believed to have high potential for the future. Although it is difficult to know with high certainty which technology alternatives those are, we suggest two nonexhaustive approaches that can be employed for this purpose: (1) focusing on a specific function and investigate a broad range of technology alternatives that can provide the function and (2) conducting cradle-to-gate studies of emerging production technologies with many potential future uses, which can be used as building blocks in future cradle-to-grave studies.

An example of the first approach is the inclusion of different transportation technologies that can be compared in terms of vehicle or person kilometres, such as fossil fuels, biofuels, hydrogen fuel, fuel cells, and electric motors (Nordelöf et al. 2014; Edwards et al. 2014). Another example is the study by Shen and colleagues (2012), where a wide selection of plastic materials was investigated: polyethylene therephthalate (PET); partially bio-based PET; recycled PET; partially bio-based and recycled PET; polylactic acid; and man-made cellulose fibers from wood pulp. Roes and Patel (2011) compared different production technologies for producing the base chemical caprolactam: via fossil benzene, via the more novel fermentation of starch or sugar cane, and an even more novel route via the chemical, 3-pentenamide. Such broad selections of technologies are likely to provide useful guidance since it is probable that at least some of the technologies will turn out to have a notable role in the future.

The second approach of conducting cradle-to-gate studies as potential building blocks has been employed in prospective LCA studies of the four carbon-based nanomaterials, graphene, carbon nanotubes, fullerenes, and nanocellulose. They can all be used for enhancing the strength of polymer materials, but some of them can also provide other properties. Nanocellulose can also provide transparency, while graphene and carbon nanotubes can provide both transparency and electric conductivity. Since it is currently unknown which of these materials will be used for which properties in which applications, a number of prospective LCA studies have assessed the cradle-to-gate impacts of these materials (Arvidsson et al. 2014, 2015; Kushnir and Sandén 2008; Li et al. 2013; Healy et al. 2008). This approach enables these studies' future use as building blocks in cradle-to-grave studies that include specific uses. An example of this is how the nanocellulose production study by Arvidsson and colleagues (2015) was used for input data to the study of nanocellulose-enforced paper by Delgado-Aguilar and colleagues (2015). Similarly, the LCA study about graphene-containing composite materials by Pizza and colleagues (2014) reported results both per kilogram (kg) graphene and per kg composite, thereby both presenting results for a specific use and providing cradle-to-gate results for graphene that could be used in studies of other uses. In the cradle-to-gate approach, it is important to report results in a way that ensures their usefulness in future studies, such as unaggregated at an inventory level. Future studies can then use the data in other combinations and employ other impact categories.

Foreground System Modeling

Once technology alternatives have been selected, the question is how these can be modeled in a relevant manner. In conventional LCA, the foreground system and production scale are modeled as they are at time t_0. In prospective LCA, the system is modeled at a future time t_f, when the production scale of the emerging technology studied has increased compared to t_0. Such modeling of the future requires the application of scenarios, which has also been suggested for LCA aiming at long-term descision making, for example, by Frischknecht (1998) and in the *International Reference Life Cycle Data System* (ILCD) handbook (JRC-EC 2010). An important aspect in prospective LCA is which future scenario the foreground system should represent and, in particular, the modeling of the future production scale (Gavankar et al. 2014). More often than not, technology performance parameters, which are often related to material and energy inputs, are functions of time and scale of production. One of the most striking examples is the reduction of the energy requirement (with a parallel reduction in materials use) of computing by 12 orders of magnitude (10^{12}) between the 1940s and 2000s (Koomey et al. 2011). Additional examples include the increased efficiency of steam engines from about 1% the 1770s to 40% in the 1970s (Ayres 1989) and the doubling of the engine efficiency of automobiles between 1920 and 1995 (Grübler 1998).

We have identified two main strategies to model the future foreground production system and scale in prospective LCA case studies: (1) predictive scenarios that illustrate environmental impacts given some likely development, including status quo, and (2) scenario ranges that are employed to illustrate the potential environmental impact, including extreme scenarios. These strategies are illustrated in figure 2. Similar scenario typologies have been described previously for conventional LCA, for example, by Pesonen and colleagues (2000) and Weidema and colleagues (2004). Although it is difficult to tell in general which of these strategies is most relevant, the relevance of predictive scenarios requires that one development is more likely than other possible developments. If no such particularly likely development exists, it is advisable to apply scenario ranges.

Different types of predictive scenarios to generate foreground data can be found in prospective LCA case studies. An example is the use of technology learning curves to predict future material inputs as utilized in a study of cadmium telluride photovoltaics by Bergesen and Suh (2016). They provide the following equation for estimating the amount of input i (mass or energy) required to produce a product j at time t_f ($a_{i,j,tf}$) (equation 1):

$$a_{i,j,tf} = a_{i,j,0}\left(\frac{\chi_{j,tf}}{\chi_{j,0}}\right)^{\beta_{i,j}} \qquad (1)$$

where $a_{i,j,0}$ is the initial amount of input (mass or energy), $\chi_{j,0}$ is the initial cumulative production, $\chi_{j,tf}$ is the cumulative production at a future time t_f, and $\beta_{i,j}$ is a learning parameter. It is also possible to predict future inputs from engineering-based scaling laws. Caduff and colleagues (2012) predicted the future
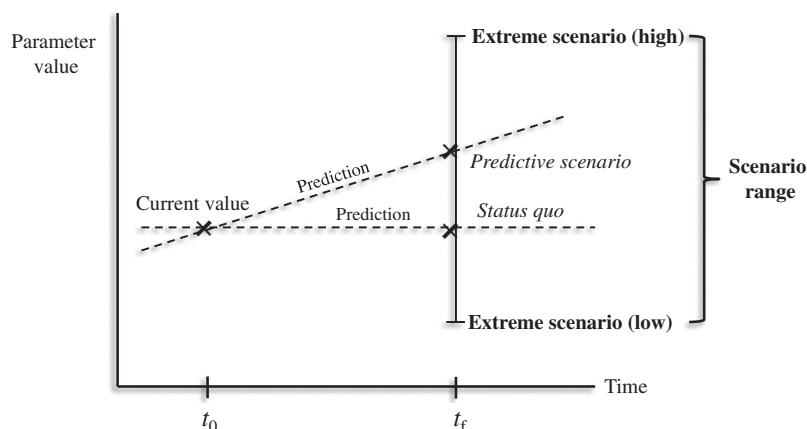
Figure 2 Schematic illustration of different scenario types in prospective LCA. Predictive scenarios are shown in italic font, and scenario ranges are shown in bold font. The symbol t_0 stands for the current time at which the study is conducted, and t_f stands for the future time at which the system is modeled. LCA = life cycle assessment.

mass inputs to wind power based on predicted increases in turbine size. For example, they used a relationship saying that the mass input of electronics and cables ($m_{e\&c}$) to a wind power plant is proportional to its height h ($m_{e\&c} \propto h$). Status quo data can also be employed in prospective LCA case studies for subsystems that are not believed to change notably within the time frame of the study. For example, Walser and colleagues (2011) used current data to model the production of a polyester T-shirt, which was subsequently treated with antibacterial nanosilver. The polyester T-shirt production was thus assumed to be conducted in the same way in the future as presently.

An alternative or complement to a predictive scenario is to apply a range of scenarios. Walser and colleagues (2011) tested ranges of values for a number of parameters related to the use phase of the nanosilver-coated T-shirt, including washing frequency, washing temperature, and the lifetime of the T-shirt. Both Walser and colleagues (2011) and Manda and colleagues (2015) investigated different production processes for the nanosilver used in antibacterial T-shirts, representing different stages of technological maturity and production scale. In their prospective modeling of ethylene production in the United States, Yao and colleagues (2015) employed expected and rapid scenarios to account for different adoption rates of emerging ethylene production technologies. Scenario ranges may include extreme scenarios that provide minimum and maximum environmental impacts. In the study of idealized large-scale production of carbon nanoparticles by Kushnir and Sandén (2008), energy use for electric heating was modeled using on the following equation for some processes (equation 2):

$$E = \frac{m c_p \Delta T}{\eta} \qquad (2)$$

where E is the energy required, m is the mass heated, c_p is the heat capacity of the material heated, ΔT is the temperature change due to the heating, and η is the energy efficiency of the heating. Assuming high efficiencies (90% to 100%), such modeling generates extreme low-impact scenarios that

are still feasible, since they stay within thermodynamic constraints. Similarly, stoichiometric relationships can be used to model minimum impact scenarios (Arvidsson et al. 2014), since they give the minimum feedstock requirements for a chemical process, provided no side reactions or other losses occur.

Several different sources have been used to provide data for both predictive scenarios and scenario ranges employed in the case studies of emerging technologies. As can be expected, data from scientific articles are frequently employed, for example, articles related to wind power and its upscaling in the study by Caduff and colleagues (2012). Patents have been used as data sources in a prospective LCA case study of graphene production (Arvidsson et al. 2014). Generally, patents can be expected to reflect production processes that are feasible and of high economic relevance (Jaffe and Trajtenberg 2002). Expert interviews is another source that has been used to obtain foreground system data in a number of case studies. In addition, experts can also guide to relevant written data sources, such as process descriptions in scientific articles and patents (Arvidsson et al. 2015). Unpublished lab results were used for foreground input data in the case of an LCA of spruce wood chips ethanol production by high-gravity processes (Janssen et al. 2016). Quantitative process simulations have been used to model large-scale production in two case studies of carbon nanoparticles and bio-based ethylene (Kushnir and Sandén 2008; Liptow et al. 2015). Such simulations can be used as a sole source of data or to verify data found in written sources. Considering the inherent data scarcity in prospective LCA (Hetherington et al. 2014), the analyst may have to be creative and turn to several of these types of sources in the same study.

Background System Modeling

Background systems can be defined as the parts of the product system that cannot be directly affected by a certain decision maker, such as the developer of a new technology (JRC-EC

2010). In conventional LCA, current background systems existing at t_0 are employed. In prospective LCA, we are interested in the background system at a future point in time t_f. The challenge in prospective LCA studies is thus to choose background systems relevant to the time at which the system is modeled. It is clear that background systems do not remain constant over time. For example, the share of renewable electricity production increased from 4% in 1997 to 24% in 2013 in Germany (Auer 2014). Furthermore, it is important to avoid a temporal mismatch between the foreground and background systems. Such mismatches have been noted in a review article on LCA studies of electric vehicles, where current background systems were often employed when assessing the electric vehicles' environmental impacts (Nordelöf et al. 2014). Although there was an ambition to assess the future impacts of electric vehicles in some of the case studies, background systems such as electricity production were assumed to be static. The same type of temporal mismatch problem has been noted in LCA case studies of energy technologies (Sandén 2008). In order to obtain relevant background system data, the same scenario approaches used to model the foreground system can be used: (1) predictive scenarios and (2) scenario ranges (figure 2). Again, predictive scenarios are valid given that some development is more likely than others—if not, scenario ranges are more relevant.

An example of a study that employed a predictive scenario for the background system modeling is a study on wheat straw ethanol production by Janssen and colleagues (2014). The current Danish energy mix was assumed as baseline, but a prediction of the changes in the Danish energy mix over time was also tested. This change mainly consisted of a reduced share of fossil energy in the energy mix (from 80% to 50%). Similarly, Zimmermann and colleagues (2015) applied predictions of the future German electricity mix in their time-resolved assessment of electric vehicles. Different authorities' forecasts can be used as a basis for predictive scenarios. Gibon and colleagues (2015) used a scenario from the International Energy Agency to model the future baseline energy production in their prospective LCA of concentrating solar power. Current background systems have been employed in a number of prospective LCA case studies, including that of wood-based ethylene (Liptow et al. 2015) and many of the studies on electric vehicles reviewed by Nordelöf and colleagues (2014). In cases when background systems are not expected to change very much, such status quo scenarios are justified. In cases when there is reason to expect that background systems will change, applying future scenarios is more relevant in order to avoid a temporal mismatch.

Scenario ranges for background systems have been applied in a number of studies. For example, Manda and colleagues (2014) employed a set of electricity mixes representing different greenhouse gas intensities when assessing a membrane filtration system for drinking water: Norwegian (low-carbon); Nordic (low-carbon); Central European (medium-carbon); American (medium-carbon); and Chinese (high-carbon) electricity mixes. Similar ranges have been employed in LCA studies of electric vehicles (Nordelöf et al. 2014). Various extreme scenarios have also been employed to test the robustness of the results. In the study of nanocellulose by Arvidsson and colleagues (2015), the current Swedish electricity production (about 50% hydro and 50% nuclear power) was assumed as baseline, but a 100% coal power scenario was also assessed as a high-impact scenario. Pini and colleagues (2017) employed the current Italian electricity mix as their baseline scenario and a completely renewable electricity mix as a low-impact scenario in their study of self-cleaning float glass.

There is one unique option for background system modeling in prospective LCA, which is not possible to apply for foreground system modeling—to omit the background systems completely. In order to avoid results based on more or less arbitrary choices of background system, the study on carbon nanoparticles by Kushnir and Sandén (2008) did not include impacts from energy background systems. Instead, secondary energy use in terms of energy carriers (heat and electricity input) was assessed. The results of that study can then be used in other settings, where specific energy background systems can be assumed depending on the goal of the study.

Recommendations and Future Work

We find that LCA can be very useful for assessing emerging technologies and for guiding early technology development, but it has to be adapted to this purpose, giving rise to a particular type of LCA methodology: prospective LCA. Recommendations for prospective LCA are summarized and contrasted to the current practices of conventional LCA in table 2. In conventional LCA, it is often relevant to consider current and near-term technologies. However, these technologies may have a marginal role in the future and may therefore be of questionable relevance to consider in a prospective LCA study. Different approaches can be taken to try to ensure a relevant selection of technologies in a prospective LCA study. Two nonexhaustive approaches are suggested in this article: (1) assessing a wide range of emerging technology alternatives that all provide the same function and (2) conducting cradle-to-gate studies of promising emerging production processes, which can later be used as building blocks in cradle-to-grave studies.

Since an emerging technology needs to be modeled at some future point in time in order to illustrate the technology's environmental performance when it is produced and used on a relevant scale, a prospective LCA will always rely on scenarios. Predictive scenarios may be employed if there is a sound basis for predictions, and, in some cases, status quo may serve as a relevant proxy for the future. If the aim is to outline potential impacts and test the robustness of results, and if the future development is difficult to predict with any certainty, ranges and extreme scenarios are recommended. There are several different data sources available for constructing scenarios in prospective LCA. Here, we recommend authors to be creative and search for data from many different sources. Scientific articles, patents, expert interviews, unpublished lab results, and process simulation are sources that have proven to be valuable in previous prospective LCA case studies.

Table 2 Summary of the recommendations in this study

Aspect	Conventional LCA	Prospective LCA
Definition	System modeled at a current or near-by time	System modeled at a future time
Technology alternatives	Currently existing technologies are studied.	Emerging technologies with relevance for the future are studied.
Foreground system data including production scale	Current foreground system and production scale are modeled. Common data sources include: • life cycle inventory databases • previously conducted LCA studies	A future scenario of the foreground system and production scale is modeled. Valuable data sources include: • scientific articles • patents • expert interviews • unpublished lab results • process simulations
Background system data	Current background system is modeled.	A future scenario of the background system is modeled. Important to avoid temporal mismatch between the foreground and background systems. Potential for not modeling background system at all.

Note: LCA = life cycle assessment.

In order to ensure the relevance of the results, it is important to avoid temporal mismatch between the foreground and background systems. Current background systems may be relevant to employ if believed to remain constant over a longer period of time. But the further ahead the saturation phase is expected to be, the more important it becomes to consider developments in background systems. We also recommend that results should be presented without the influence of background systems, or with background system impacts reported separately, in order to allow reuse of the study in alternate contexts.

A particularly important area for future work is the development of predictive scenarios, especially for the foreground system. Finding generic scale-up and scenario prediction approaches for cases when scenario ranges are not considered adequate is challenging, but would be very useful for prospective LCA studies. As mentioned above, Bergesen and Suh (2016) used learning curves in a generic approach to predict future inputs of mass and energy (equation 1). However, learning curves generally have shortcomings due to high uncertainty (Rubin et al. 2015). A minor uncertainty in the learning parameter would propagate into high uncertainty in calculated environmental impacts. Whether learning curves can provide reliable predictions for prospective LCA is thus an item for future research, along with the investigation into other generic scenario prediction approaches.

Another aspect for future research is the impact assessment step in prospective LCA studies, which we have given no attention to in this paper. Emerging technologies may give rise to new types of environmental problems, such as emissions of nanomaterials (Hischier 2014). Other environmental problems may have declined in the future. This means that some impact categories that may be relevant for assessing emerging

technologies do not exist yet, whereas some that do exist may not be so relevant. In addition, several papers have shown that correlation between impact categories is generally high and that a limited set of impact categories is often sufficient to describe the environmental impact of a product (Huijbregts et al. 2006, 2010; Pascual-González et al. 2015; Janssen et al. 2016; Steinmann et al. 2016, 2017). If such a limited set was found sufficient for emerging technologies, it would be convenient in order to reduce data requirement. Overall, we find that the selection of impact categories in prospective LCA is an area that warrants further investigation.

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