Environmental sustainability of NdFeB magnet recycling: foresight study on recycling systems and technologies

Nielen S.S. van

5 Accounting for learning in prospective LCA: Theory and practical guidance

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Abstract

Learning is important for the development of industrially deployed technologies, and learning curves have been used to determine future production costs. Although the effect of learning on costs has been extensively studied, very little evidence exists for its effect on environmental impacts, and a conceptual underpinning is lacking. Based on a review of theoretical foundations and empirical evidence, this study presents a procedure for assessing learning of industrial processes in ex-ante and prospective life cycle assessment (LCA). We argue that learning involves operational or organizational changes, which are motivated by incentives. Therefore, environmental impacts may follow a learning curve trend if the origins of impacts coincide with dominant incentives. A key observation is that the results may vary by impact category, and certain impacts may not decline at all. We developed guidelines to evaluate environmental learning effects and rates, and illustrated these with examples in an LCA context. Further research is needed to expand the evidence base for environmental effects of learning, by re-interpreting datasets of existing technologies to determine their learning rates.

5.1 Introduction

5.1.1 Anticipating future environmental performance

New technologies are rapidly being developed, which is crucial for shaping a sustainable society. Especially for breakthrough technologies with a large deployment potential, it is important to understand potential efficiency gains and the associated timeframe resulting from learning, optimization, and upscaling. These insights direct investments towards environmentally more promising technologies, aiding investment planning and decision-making (Sandén & Karlström, 2007).

Technological learning is the improved performance of a product or process over time due to increasing experience and knowledge. It has been identified as one of the mechanisms responsible for decreasing environmental impacts, mainly for mature technologies (Junginger et al., 2008). Technology forecasting guidelines (NETL, 2013; Roussanaly et al., 2021; Rubin, 2019) distinguish a formative phase with fundamental technology changes, followed by an industrial deployment phase with incremental and more predictable development driven by learning. The industrial phase typically starts at technology readiness level (TRL) 9. Learning at the level of individuals, teams, companies, and sectors is a key to achieving sustainability goals (Feeney et al., 2023). For instance, technological learning reduced emissions for the production of solar panels (Kavlak et al., 2018; Louwen & van Sark, 2020), metals (Gutowski et al., 2013), and chemicals (Ramírez & Worrell, 2006). This paper addresses these learning effects.

Learning can significantly improve industrial technologies, but solid evidence only exists for the economic implications. In business economics, learning curves refer to the phenomenon of decreasing costs of production. The downward trend of costs as a function of cumulative production is strongly supported by empirical evidence, both for companies and for industrial sectors (Dutton & Thomas, 1984). It has been postulated that the effect of learning on environmental impacts ('environmental learning') resembles the effect on costs (Faber et al., 2022; Thomassen et al., 2020; van der Hulst et al., 2020). However, evidence and justification are lacking, as explained below. For either learning curve, tracing causality is difficult (Grubb et al., 2021; Kavlak et al., 2018).

5.1.2 Missing insight in environmental learning curves

To assess the future environmental impacts of novel technologies, several ex-ante life cycle assessment (LCA) modelling practices have been developed (Arvidsson et al., 2018; Buyle et al., 2019; Thomassen et al., 2019; Tsoy et al., 2020; van der Giesen et al., 2020). Good guidelines exist for the formative phase of technology innovation, extrapolation of lab-scale data to large scale, and for modelling background systems (Thonemann et al., 2020; Tsoy et al., 2020). Yet, the subsequent industrial phase, including learning and scaling effects, has been addressed by only few LCA-related studies (Buyle et al., 2019; Caduff et al., 2012; Thomassen et al., 2020; van der Hulst et al., 2020), and a comprehensive approach is lacking for predicting these effects.

A major uncertainty is if and how cost-based learning curves can be translated to environmental learning curves (Buyle et al., 2019). Bergesen & Suh (2016) and Thomassen et al. (2020) suggest that technological development is the main driver for both costs and impacts, as illustrated by the middle column in Table 5.1. However, this is challenged by examples of purely cost-oriented learning effects (Table 5.1, left column) and design trade-offs between costs and emissions (Table 5.1, right column). These cases indicate a disconnect between costs and emissions. Furthermore, it is uncertain whether learning can be generalized to other products, industries, or impact categories. Various environmental impacts often arise from different processes, each process with a distinct learning trend. Therefore, extrapolating learning curves from one impact category to another requires careful consideration. Thomassen2020 provided guidelines for technological learning without differentiating between impact categories, leaving unclear what environmental impact is affected. van der Hulst et al. (2020) constructed a learning curve for greenhouse gas (GHG) emissions, questioning if other impact categories would show a similar correlation.

TABLE 5.1: Learning effects, grouped by economic and environmental consequences.

Factors that decrease costs with minimal environmental effects [a]	Technology changes with both environmental and financial benefits	Technology changes with environmental benefits, possibly increasing costs
Budget overruns due to delays Cost of capital (interest payments) Regulatory fees (permitting) Commercial and legal risk mitigation Insurance costs Overhead costs Marketing costs for new products Single orders rather than bulk purchases	Improved resource and energy efficiency of processes (Bergesen & Suh, 2016) Improved design of process equipment (Arundel et al., 2008) Improved use-phase efficiency (Weiss et al., 2010) Higher equipment utilization and lower depreciation (Rubin, 2019)	End-of-pipe solutions (Frondel et al., 2004) Product improvement to meet the preferences of environmentally conscious consumers (Cai & Li, 2018) Shift to inputs [b] or suppliers with lower impacts (Bergesen & Suh, 2016) Material or process substitution (Ferioli et al., 2009)

[a] Source: Roussanaly et al. (2021); Santhakumar et al. (2021)
[b] Inputs include feedstock materials, energy carriers, and equipment.

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5.1.3 Research aim and approach

The objective of this paper is to investigate how learning effects influence environmental impacts, and to develop an approach to assess environmental learning in product systems. We combined a review of empirical results with an investigation of the theoretical foundations and driving mechanisms of environmental learning. Based on these insights, we aim to develop recommendations to guide forward-looking LCA studies. Specifically, our guidance addresses two questions: 1) Is a learning curve expected for a given environmental impact category? 2) How can the learning rate be quantified?

This study considers learning effects on the market-average environmental impacts of specific products, rather than product categories. The scope is limited to industrial goods, manufactured products with a TRL $\geq$ 9, and commodities, thus excluding services. We focus on patterns at a sector-level rather than the level of individual firms or economy-wide dynamics.

This paper argues that environmental learning curves do not always follow the trend as costs, but can be explained by technology changes that are motivated by external incentives. §5.2 provides an overview of the concept of learning, learning mechanisms and their role in technology development. §5.3 presents a systematic procedure to account for learning in ex-ante LCA studies, illustrated by examples in §5.4.

5.2 Technological learning theory and evidence

5.2.1 Overview of technology development

Research into the future impacts of emerging technologies has revealed several technology development mechanisms, that operate in both the formative and industrial phase. van der Hulst et al. (2020) identified five mechanisms: process changes, size scaling, process synergies, industrial learning (or technological learning) and external developments. Buyle et al. (2021) additionally introduces technology diffusion. Based on the literature, Figure 5.1 illustrates the various mechanisms and the maturity levels at which they become active.

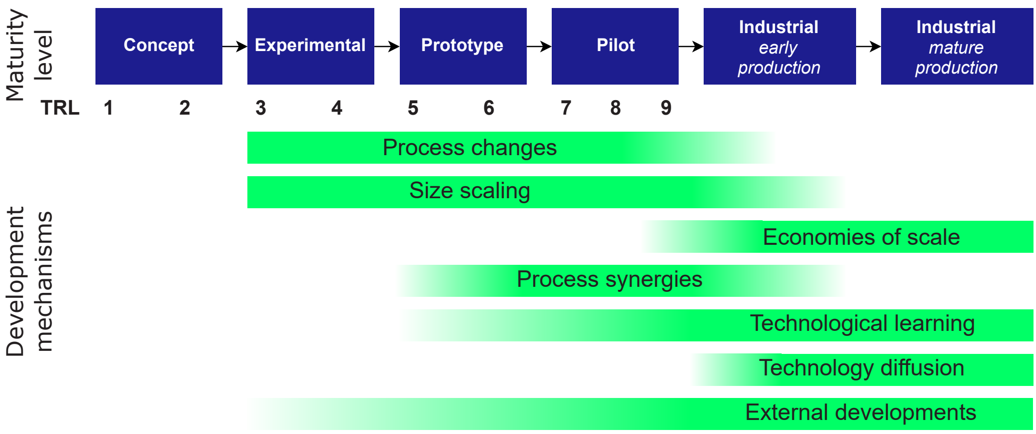

FIGURE 5.1: Stages and mechanism in technology development. Technological learning is also referred to as industrial learning. TRL, technology readiness level. Based on Buyle et al. (2019); van der Hulst et al. (2020).

Except for technology diffusion and external developments, each mechanism implies changing the process or its operation by workers. These changes become more incremental as the maturity increases, partly because the low-hanging fruit for optimization has been picked and partly due to tighter integration with the industrial ecosystem. Figure 5.1 distinguishes between size scaling of unit processes and economies of scale due to company size. These scaling effects are often included in the learning effect because they occur simultaneously and are interconnected (Dutton & Thomas, 1984; Kavlak et al., 2018).

Besides classifying technology developments as process-level changes (Figure 5.1), they can also be differentiated by organizational mechanisms. These include technology adoption (installing improved equipment), novel knowledge combinations, imitation and reverse engineering (Arundel et al., 2008), and knowledge spillovers from other companies (Clarke et al., 2008). Technological learning mechanisms include learning-by-doing, learning-by-using, learning-by-interacting, and R&D (Junginger et al., 2008).

5.2.2 The learning curve

In cost-based learning studies, the mechanisms of technology development during the industrial phase are combined into a continuous trend. This trend is most often described by Equation 5.1 (Dutton & Thomas, 1984). According to the equation, production costs per unit C decline from the initial level C_0 as a function of the cumulative production P (in units or kg). Here, P_0 is the initial production, and exponent a defines the slope of the learning curve (negative values indicate a downward trend) (Dutton & Thomas, 1984). Eq. 5.2 defines the learning rate (LR) as the percentage cost reduction after a doubling of cumulative production.

$$C = C_0 \cdot \left(\frac{P}{P_0}\right)^a \tag{5.1}$$

$$LR = 1 - 2^a \tag{5.2}$$

Eq. 5.1 allows to extrapolate historical trends, with greater accuracy if more data points are available. The log-linear relation applies from TRL 9 onwards, as underlined by C_0 which is the cost of the first unit produced (Rubin, 2019).

Historic data are often unavailable for emerging technologies, therefore alternative approaches have been developed. Santhakumar et al. (2021) recommend to combine a bottom-up cost model (to identify cost drivers) and a component-based learning curve. This implies that the costs are broken down by constituent parts or processes, each of which is modelled by its own learning curve (Ferioli et al., 2009). The component learning rates can be based on similar technologies (proxies). Alternatively, the decomposition approach introduces a separate learning curve for each upstream process, which sum up to a combined learning trend (Kavlak et al., 2018; Nadeau et al., 2010). As Eq. 5.1 indicates, processes with a longer production history tend to progress slower for a given increase of cumulative production. Decomposition is based on the actual supply chain, whereas component-based learning looks at similar technologies and components. Both approaches provide a detailed view of the learning effects on components. For more developed technologies, other approaches exist (see Appendix D.1.1).

5.2.3 The technological learning process

Learning in industrial and organizational context is a change in behavior that aims for improved performance (Sterman, 2002). The concept of learning originates from behavioral sciences, where it describes how individuals and organizations gain experience over time (Fiol & Lyles, 1985; Lapré et al., 2000). Organizational learning is defined as the process of creating, acquiring and transferring knowledge and changing behavior accordingly (Fiol & Lyles, 1985).

During the learning process (Figure 5.2), technology changes—whether radical or incremental—are implemented in response to perceived effects and the operator's motivations. Although inventions and opportunities for improvement may emerge serendipitously, their adoption is a deliberate decision (Chandler & Hwang, 2015). Even if unconscious changes occur, they are influenced by stakeholder demands and market pressures, shaping the proliferation of technologies. Technology change involves new working practices, implying organizational or behavioral change (Dutton & Thomas, 1984). These changes require a motivation to overcome the inertia of entrenched practices.

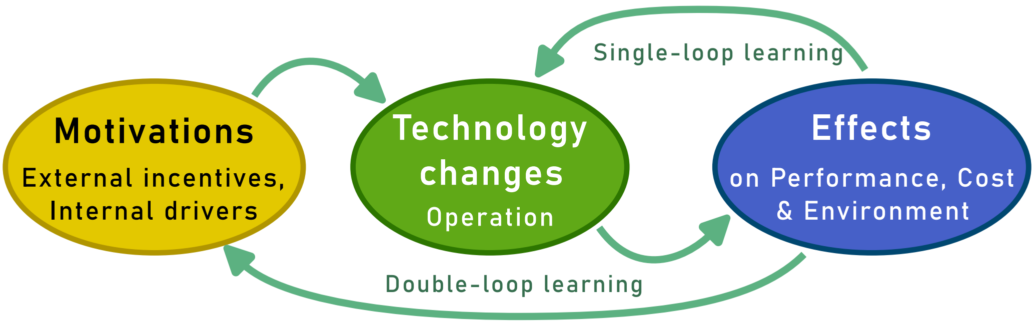

FIGURE 5.2: Schematic representation of learning in technology development, inspired by the conceptualization of organizational learning by Argyris & Schön (Fiol & Lyles, 1985).

Given this context, to know the direction and rate of changes from learning, it is important to understand the prevailing incentives. As Figure 5.2 illustrates, the effects of a technology are evaluated against an actor's motivations, resulting in a decision to change or not. Motivations for individual employees consist of recognition and reward policies and their personal drivers. Motivations for companies and sectors are market selection criteria and other stakeholder pressures, as these determine the success and proliferation of companies (Henderson & Stern, 2004). Stakeholder pressures can incentivize cost reductions but also enhance other indicators like aesthetics, safety and performance (McCollum et al., 2017). These motivations can often be translated to management performance indicators (KPIs). §5.2.4 elaborates on each element in Figure 5.2.

5.2.4 From motivations to environmental effects

5.2.4.1 Motivations

Due to learning, products or processes can develop lower environmental impacts if this aligns with the dominant motivations. Environmental effects can result either directly (intentional impact reduction) or indirectly (as side-effect of pursuing other goals). In many mature markets, motivations for cost reduction dominate. This explains the high predictive value and wide applicability of cost-based learning curves. Gradual trends emerge due to relatively constant prices and cost pressures. In almost all decisions in industrial companies, costs are considered (Merchant & Shields, 1993). However, not all decisions lead to lower cost, because other product attributes also play a role (McCollum et al., 2017).

On longer time scales, motivations can change as a result of double-loop learning, i.e. learning with respect to goals and values (Fiol & Lyles, 1985). As Figure 5.2 indicates, double-loop learning involves changing motivations, sometimes mediated by shifting stakeholder pressures. Double-loop learning, also referred to as *transformative learning*, applies to systems involved in a societal transition (Feeney et al., 2023; Lankester, 2013). These transitions are difficult to predict, adding uncertainty to the analysis.

Sections 5.2.4.2 and 5.2.4.3 review the types of motivations, as uncovered by eco-innovations literature. Although eco-innovation is different from environmental learning (the former emphasizes the novelty of changes), the motivations for both most likely overlap. We distinguish between external incentives (from stakeholder pressures) and internal drivers. External incentives are most relevant for industry-wide trends of learning, while internal drivers help to explain the differences among organizations.

5.2.4.2 External incentives

In general, company decisions—also those affecting environmental impacts—are influenced by market pressures, e.g. competitive forces (Porter, 1979) and institutional pressures (DiMaggio & Powell, 1983). For eco-innovations, these incentives have been classified based on various theoretical backgrounds. Nevertheless, different studies have identified broadly similar sets of drivers (Hojnik & Ruzzier, 2016). Based on established theoretical frameworks (Cai & Li, 2018; Hojnik & Ruzzier, 2016), five groups of external incentives can be distinguished: customer preferences, competitive pressure, restrictive environmental regulation, market-stimulating regulation, and investor and partner preferences.

These pressures are exerted by stakeholders on a producing company. Normative pressure is exerted by customers, and also emerges in institutional forms from investors, value chain partners and societal organizations. Organizations have to comply with societal norms if they want to ensure their legitimacy and access to resources (Hojnik & Ruzzier, 2016). Besides, shareholder value may be created by avoiding environmental risks and liabilities (Sarkis et al., 2010). Governments can apply restrictive or market-stimulating regulation. Competitive pressure can encourage adoption of technologies used by others (DiMaggio & Powell, 1983).

The importance of different drivers was determined by several empirical studies. For instance, eco-innovation was found to correlate with competitive pressure, market-stimulating regulation, and customer green demand for Chinese companies (Cai & Li, 2018). Five major drivers were reported for eco-innovation in Germany: existing and expected regulations, voluntary codes and industry agreements, customer demand, and competitor moves (Horbach et al., 2012). These incentives affected various environmental impacts differently. Cost savings are an important motivation for reducing energy and material use, while regulations mostly encourage lower air, water and noise emissions, and customer requirements influence impacts related to waste and hazardous substances (Horbach et al., 2012).

5.2.4.3 Internal drivers

Next to external incentives, learning is influenced by company-internal factors (Hojnik & Ruzzier, 2016). Already in 1984, it was noted that "the learning rate is neither fixed nor automatic, leading to the question how it is managed best" (Dutton & Thomas, 1984). Cai & Li (2018) distinguish two types of internal drivers: organizational capabilities and technological capabilities. Managers are responsible for defining sustainability KPIs and integrating them into business models (Schaltegger et al., 2012), supported by (physical) resources and environmental management systems (EMSs) (Sarkis et al., 2010). Differences in management, intrinsic motivation and internally-defined performance targets lead to deviations from the average market trend.

For energy efficiency in manufacturing companies, empirical studies confirm the importance of organizational and management variables (Solnørdal & Foss, 2018). A relevant finding for sector-level learning trends is that "innovation breeds innovation" (Cai & Li, 2018), i.e., organizations can use the capabilities gained during a learning process to capture further opportunities. Therefore, more innovative sectors may respond faster to incentives and exhibit higher learning rates.

5.2.4.4 Technology changes

In response to the motivations described above, operational or technological changes can be made that reduce environmental impacts (see Figure 5.2). Learning can alter any operational parameter. Parameters with environmental effects include energy use, material use, waste or discards, equipment use, waste treatment or use-phase efficiency. Some effects are unintentional, for example, manufacturers may replace a material for aesthetic reasons, while the new material has lower or higher environmental burdens. Examples of technology changes are listed in Table 5.1.

A specific technology change is the upscaling of production capacity. In line with Figure 5.2, the pursuit of economies of scale (motivation) leads to upscaling (technology change), resulting in cost reductions (effect). Scaling typically provides environmental benefits, although diseconomies of scale also occur (Wilson, 2012). Upscaling and learning are intertwined, because the experience gained from demonstration plants is essential to develop a process at larger scale, as exemplified by wind turbines (Caduff et al., 2012). Additionally, faster material processing due to learning would increase the production capacity, particularly for modular technologies (Wilson et al., 2020).

5.2.4.5 Effects on performance, cost, and environment

Technology changes in products and processes can have both positive and negative environmental effects. Manufacturers may respond to stakeholder pressures, including preferences for certain product characteristics. Some characteristics align while others conflict with sustainability performance. For instance, the consumer preference for larger passenger vehicles and refrigerators has resulted in decreasing energy efficiency during certain time periods, whereas the efficiency increased during other periods (Dahmus, 2014). Besides, process innovations may have diverging effects across environmental domains (Chen et al., 2022; Kammerer, 2009).

In specific cases, the prevailing incentives may lead to increased emissions. For example, customers can prioritize a low price, neglecting external costs. Alternatively, customers can prefer higher performance (better resolution, larger products). Competitive pressures can provoke mimicry of competitors and a return to conventional practices. Local regulation can cause burden shifting to other regions or impact categories. Burden shifting may also result from substitution of raw materials or processes (Yu et al., 2016). For instance, a raw material can be replaced by a cheaper but more polluting alternative, while process automation may reduce waste and space occupation, but requires more energy and machines (Moreau et al., 2021).

Some learning effects only or predominantly influence costs, while economic and environmental benefits can also be achieved simultaneously (Table 5.1, left and middle column). E.g., cost-driven industries with high energy intensity invest more in energy efficiency (Kalantzis & Niakaros, 2020), boosting environmental learning for fuel-related emissions.

5.2.5 Evidence for environmental learning

Thomassen et al. (2020) reviewed 105 studies on technological learning, identifying only four studies that used or derived a learning rate for the environmental impact: Görig & Breyer (2016); Louwen et al. (2016); Stamford & Azapagic (2018); and Yuan et al. (2018). We identified eight more studies[1] using Google Scholar and the keywords in Appendix D.2, and review these below. The sample size of 12 papers is sufficient for this conceptual paper, as it is not a systematic review.

Eight of twelve reviewed studies assessed only a single environmental indicator. The most common indicator was energy consumption ('cumulative energy demand' or 'specific energy consumption', in 7 studies), followed by GHG or CO_2 emissions (3 studies). Only Stamford & Azapagic (2018) systematically studied a range of impact categories using LCA, and found a different trend for each impact category. Except for CO_2 absorption, all technologies had a TRL above 9. Besides, it is remarkable that five studies investigated photovoltaic (PV) technology.

The learning rates varied widely, as shown in Figure 5.3 for the reviewed studies. Even for a single indicator, reported learning rates vary significantly, ranging from 3% to 29% for energy use across products. Interestingly, this range largely coincides with the learning rates reported for use-phase energy consumption, $18 \pm 9\%$ (Weiss et al., 2010). The differences partly arise from the functional unit definition (area or rated power of PV panels) and whether the thermodynamic minimum is considered (Ramírez & Worrell, 2006) (see §5.3.5).

For material use and waste generation, the learning rate varies depending on the material. PV manufacturers have reduced the need for silver more than the need for silicon (Louwen & van Sark, 2020). These results align with the conceptualization of learning discussed above. For the early PV industry, strong incentives existed for cost reduction, therefore the more valuable silver input was reduced more strongly. Additionally, improved power production efficiency contributed to a decrease in costs per functional unit (the peak power output) (Kavlak et al., 2018; Louwen & van Sark, 2020).

[1] Bergesen & Suh (2016); Brucker et al. (2014); Gutowski et al. (2013); Hettinga et al. (2009); Lapré et al. (2000); Louwen et al. (2020); Ramírez & Worrell (2006); Rochedo & Szklo (2013)

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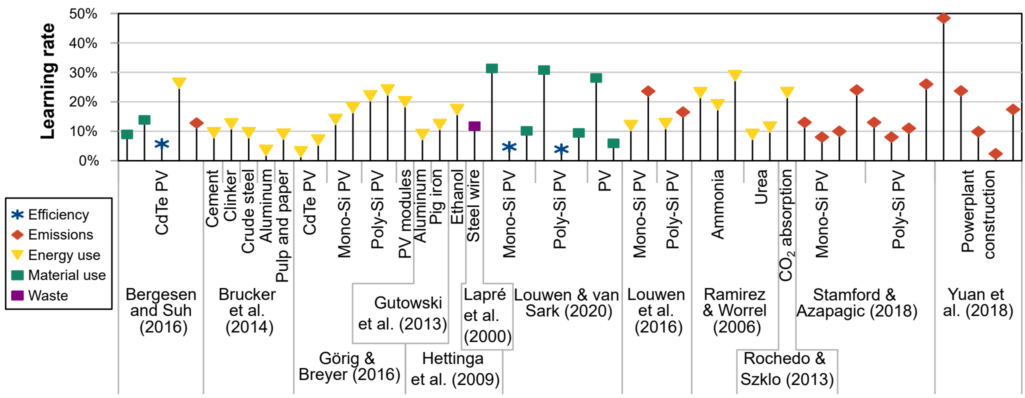

FIGURE 5.3: Learning rates for environmental indicators, as derived in literature case studies. The learning rate is the impact reduction after a doubling of cumulative production (see Eq 5.1).

5.3 Accounting for learning in LCA

Drawing from the insights in §5.2, we developed a procedure for evaluating environmental learning effects. Figure 5.4 outlines the six involved steps, which are elaborated below. As in any LCA, the first step is a scope definition. The learning rates of supply chain processes may vary (§5.2.2), while environmental hotspots differ across impact categories. Therefore, step 2 identifies these hotspots. Learning is driven by incentives arising from stakeholder pressures (§5.2.3), as analyzed in step 3. Step 4 compares these incentives to environmental hotspots, to determine if environmental learning is expected. Step 5 quantifies the learning rate, enabling LCA practitioners to incorporate technological learning effects in prospective assessments. Estimates of future impacts involve uncertainty, which is assessed in the final step.

5.3.1 Define the scope

The scope is defined by choosing an industrial product and an impact category. Since processes with a short production history progress faster, these should be included in the foreground system. Note that the appropriate scope of a process varies from case to case. It can be a single unit operation if the operations have diverging TRLs, or a whole manufacturing line.

5.3.2 Assess environmental hotspots

Next, LCA is used to calculate the product's life cycle environmental impacts. For technologies with low TRL, other ex-ante LCA methods should be used first to estimate the performance at industrial scale (TRL 9). Then it is possible to identify the environmental hotspots and their link to a foreground process or its inputs. The hotspot analysis determines which environmental impacts have common origins. If the burdens of multiple

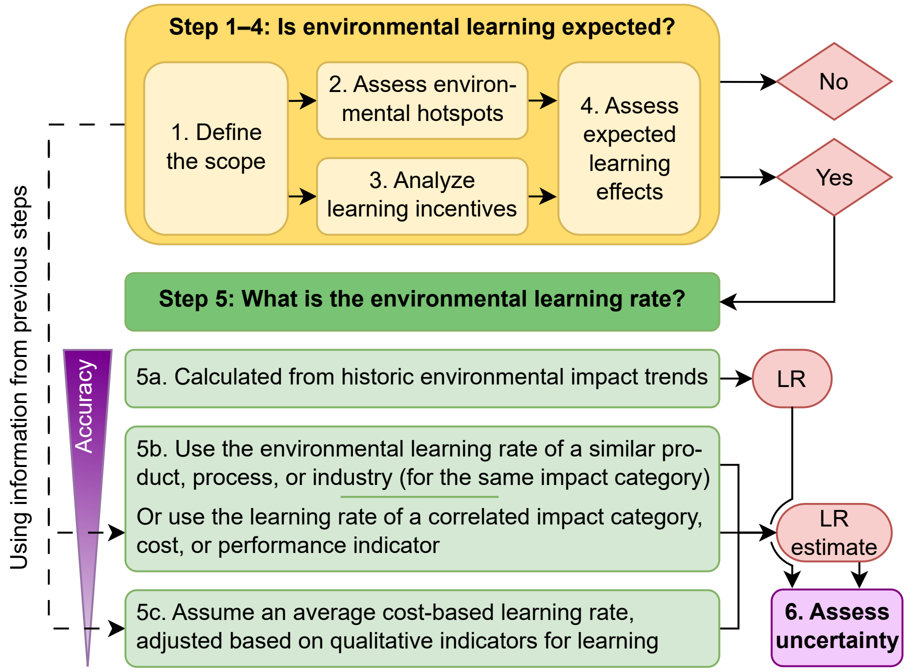

FIGURE 5.4: Overview of the procedure for evaluating environmental learning effects in LCA. The diagram shows connections between the 6 steps and, for step 5, the preference order of alternative approaches are shown. LR: environmental learning rate.

categories originate from a shared process (e.g. fuel combustion) or the same material (e.g. the supply of a metal), their trend will be similar.

5.3.3 Analyze learning incentives

Stakeholders that influence the foreground system can be identified by considering six groups: consumers, regulators, investors, competitors, societal organizations, and value chain partners. Then, the main incentives for the operator of the foreground process are determined, ideally through stakeholder interviews. Relevant drivers were described in §5.2.4.2. If changing motivations (§5.2.4.1) introduce uncertainty, multiple scenarios may be developed.

5.3.4 Assess expected learning effects

This step inspects the link between environmental hotspots (from step 2) and incentives experienced by the responsible actors (step 3). If both are linked to different processes or inputs, no environmental learning is expected. If both are linked to the same processes or inputs, environmental learning is expected to occur. If incentives or KPIs derived from them represent a trade-off with environmental impacts, a negative learning rate is expected (as discussed in §5.2.4.5). If technology diffusion and size scaling introduce economies of scale for hotspot processes, the environmental learning rate is positive. Extensive analyses may repeat this step for additional hotspots or stakeholders.

5.3.5 Estimate learning rate

If step 4 concludes that learning effects are plausible, the learning rate can be estimated. The estimation can use one of the following three approaches, depending on data availability. These are similar to approaches for cost-based learning. The estimates can be adjusted upwards or downwards based on the learning incentives analyzed in step 3.

a. Using historical data

The most straightforward approach uses historical data to determine the environmental learning rate. Records of past impacts are fitted to Eq. 5.3, allowing to extrapolate future trends. Analogous to Eq. 5.1, I_0 is the environmental impact of the initial production volume P_0, and the time-dependent variables are cumulative production P and environmental impact I (e.g. emission per kg product).

$$I = I_0 \cdot \left(\frac{P}{P_0} \right)^a \tag{5.3}$$

Some impacts are bounded by thermodynamic limits, e.g. the minimum land area or energy needed. In those cases, Eq. 5.3 should be adjusted to enforce the lower limit of impacts I_{min} (Ramírez & Worrell, 2006), as in Eq. 5.4.

$$I = I_{min} + I_0 \cdot \left(\frac{P}{P_0} \right)^a \tag{5.4}$$

Novel upstream processes should either be considered as part of the main process or be addressed by a decomposition approach, introduced in §5.2.2. This is because the main process can contribute to significant demand growth of a material, driving upstream learning and development (Bergesen & Suh, 2016). This effect was observed in the PV supply chain (Kavlak et al., 2018).

b. Using a proxy

Secondly, the environmental learning rate of a similar product, process, or industry can be assumed, e.g. based on §5.2.5. Alternatively, the learning rate of an impact category can be estimated by referring to another impact category, cost, or performance indicator (e.g. energy efficiency), if the two are correlated. The correlation is revealed in step 2 and 4. Groups of correlated impact categories may occur (Esnouf et al., 2019), although the distinct learning rates will vary (Stamford & Azapagic, 2018).

As a cost-based proxy, over hundred industry-specific learning rates are available (Balasubramanian & Lieberman, 2010) Appendix D.3.6). Alternatively, aggregated averages are $19 \pm 8\%$ for industrial products, $16 \pm 9\%$ for energy supply technologies, and $18 \pm 9\%$ for use-phase energy consumption (Weiss et al., 2010). However, cost-based learning is unsuitable as proxy if cost reductions can be primarily attributed to purely financial factors (Table 5.1). Besides, such analysis should correct for material price fluctuations (Thomassen et al., 2020).

Extrapolated learning curves address both learning and scaling effects. However, if the scaling behavior differs between the target and proxy technology, scaling effects should be modelled separately using empirical scaling laws or theoretical models (Caduff et al., 2012, 2014; Piccinno et al., 2016), see Appendix D.1.2.

c. Using sectoral averages

The third approach obtains a rough estimate based on sector-specific characteristics that tend to foster a high learning rate: agility (exemplified by the sector's ability to innovate in the past), repetitiveness of manufacturing, potential for automation or economies of scale, and substitutability of the hotspot process or input (see §5.2.4.4). Also, higher learning rates are expected when the incentives are more aligned with (un)intentional impact reduction (step 4). Based on these factors, the learning rate can be adjusted towards the lower or higher end of reported ranges (Weiss et al., 2010). Although this is the least preferred option, it might be the only method for emerging technologies.

5.3.6 Assess uncertainty

Learning curves are a type of extrapolation, associated with uncertainties. Prior to extrapolation, step 1–4 aim to verify if an environmental learning curve is expected. Due to limited availability of empirical data (see §5.2.5), proxies for environmental learning should be used with caution.

To assess uncertainties, environmental learning can be included in scenario-based LCA studies. Scenario narratives becomes more detailed by integrating stakeholder pressures, incentives (described in §5.2.4) and technological changes (§5.2.4.4). Learning rates can be adjusted in line with other scenario assumptions. Further guidance on addressing uncertainty in ex-ante LCA is provided by van der Giesen et al. (2020).

Uncertain technology performance demands for contingency measures. Therefore, ex-ante cost evaluations often introduce contingency factors, that increase the bare cost estimate by a fraction depending on the maturity (AACE, 1991; Rubin, 2019). Contingency costs decrease with experience, and account for e.g. failed batches, unexpected down-time, and additional steps or safety measures. These unplanned deviations are rarely included in (ex-ante) LCA studies, therefore this approach could contribute to more realistic environmental assessments.

5.4 Illustrative examples

5.4.1 Implications for specific product types

Bulk goods and mass products are mostly subject to cost reduction incentives. By definition, this applies to commodities (Merriam-Webster, 2023). If energy is the main expenditure, fuel-related emissions are likely to decline (e.g. Gutowski et al., 2013). If materials are the main cost driver, impacts related to the material production could decrease.

Environmental impacts of waste management may not exhibit learning effects, unless impacts of waste are internalized.

For consumer products, customer preferences influence the learning process. Important aspects are price, product quality and ease of use (Jayasinghe, 2016). If these preferences induce material substitution, burden shifts are expected. If most impacts originate from a material, while consumers prefer more material-intensive products (e.g. larger smartphones or refrigerators) (Dahmus, 2014; Kasulaitis et al., 2015), negative learning may occur. If the main criterion is the product price, the trends of bulk goods apply. However, if the production costs are largely associated with labor, environmental learning may be absent. Since consumer preferences are variable, learning rates in this sector are more uncertain.

Manufactured products consisting of many elements are typically developed to meet consumer needs of functionality, usability, and durability, next to investor incentives for cost minimization. This leads to minimization of manufacturing time. One way is automation, resulting in higher impacts related to metals production for machines and possibly lower losses of feedstock materials (Moreau et al., 2021). Another way is greater labor efficiency, leading to lower impacts from operating manufacturing buildings.

Agricultural products (food and biofuels) are expected to display learning with respect to land use, due to a high cost of labor and land and due to a focus on productivity (Taramuel-Taramuel et al., 2023). Agriculture faces a clear trade-off between efficient land use (high crop yield) and nutrient emissions. In many countries, the costs of fertilizers outweigh the costs of land use, resulting in increasing nutrient emissions (Zhang et al., 2015). In the case of high fertilizer costs or strong policy incentives, emissions of nutrients and pesticides might decrease.

Different trends are expected for small pollutants not related to energy production, such as heavy metals or carcinogens. Price-driven industries will not naturally address these substances. Regulatory, societal or supply-chain pressure can induce material substitution or end-of-pipe solutions.

5.4.2 Procedure applied to copper

Box 5.1 demonstrates the procedure in Figure 5.4 for the case of copper production, to determine the expected environmental impact trends. Copper production is an established process, hence sufficient data is available for the analysis. The main data source is ecoinvent 3.9.1 (cut-off version) (Wernet et al., 2016). This database provided unit process data and prices in 2005-Euros. The functional unit is 1 kg copper from the global "market for copper, cathode". An LCA was conducted using Brightway 2.4.3 (Mutel, 2017). The life cycle impact assessment methods were obtained from Environmental Footprint method 3.0 (Fazio et al., 2018). In step 3, costs are calculated based on the LCA model. Note that ecoinvent assigns an economic value of zero to waste. In reality, waste treatment entails levies or taxes. Still, this analysis is based on ecoinvent data for illustrative purposes.

Box 5.1: Example of environmental learning assessment applied to copper. The LCA approach is described in the main text.

1. **Define the scope:** The global market mix of copper, and its impact in seven impact categories (Climate change, Acidification, Freshwater ecotoxicity, Freshwater eutrophication, Human toxicity: cancer, Human toxicity: non-cancer, and Tropospheric ozone).

2. **Assess environmental hotspots:** The LCA results in Figure 5.5 show several hotspots depending on the environmental impact category. Smelting is a hotspot for human toxicity and acidification, mine tailings are a hotspot for freshwater eutrophication and ecotoxicity, and electricity contributes most to climate change.

3. **Analyze learning incentives:** The main stakeholders are shareholders of mining companies and wholesale purchasers. Copper is a commodity, and the main driver for the supply chain is cost reduction. The calculated costs of €3.74 per kg copper are broken down in Figure 5.5.

4. **Assess expected learning effects:** Cost reduction aligns most with reduced climate change impacts. For both costs and climate change, important drivers are electricity and fuels. Therefore, learning is most likely to reduce climate change impacts.
   Copper smelting is a hotspot for acidification and human toxicity effects (cancer and non-cancer), while the process causes around 5% of the costs. There are no cost incentives for smelting to reduce the emissions to air and water. Moreover, technologies to avoid pollution by tailings and exhausts are more costly (Lèbre et al., 2017). Hence no learning curve is expected for human toxicity impacts. This may change when pressures arise from e.g. local communities or governments to address pollution. Similarly, no learning effects are expected for freshwater ecotoxicity and eutrophication. These impacts originate primarily from mine tailings, which are disposed of at very low costs.
   Finally, waste recycling bears significant costs, while causing minimal environmental burdens. Therefore, it is expected that recycling will increase if the availability of copper scrap allows, leading to greater added value and reduced environmental impacts. The recycled content is not solely determined by learning processes, since it is limited by physical constraints.

5. **Estimate learning rate:** Historical data is available for GHG emissions of primary copper production (Rötzer & Schmidt, 2020). Although ore grades have declined over time, we assume a constant grade of 1.7% to make a functionally equivalent comparison. These data are combined with the cumulative production (Porter et al., 2018). Finally, the parameters of Eq. 5.3, are fitted to the data, yielding a learning rate of 23% for GHG emissions.
   No historical data are available for tropospheric ozone formation, but it may exhibit learning due to some alignment with costs. We use the sector-average learning rate for costs. The relevant sectors are primary and secondary smelting and refining of nonferrous metals, corresponding to SIC 333 and 334,

which have respective learning rates of 24.1 ± 5% and 21.4 ± 5% (Balasubramanian & Lieberman, 2010). Because of the partial overlap with cost reduction, the estimated learning rate is towards the lower bound, at 18%.

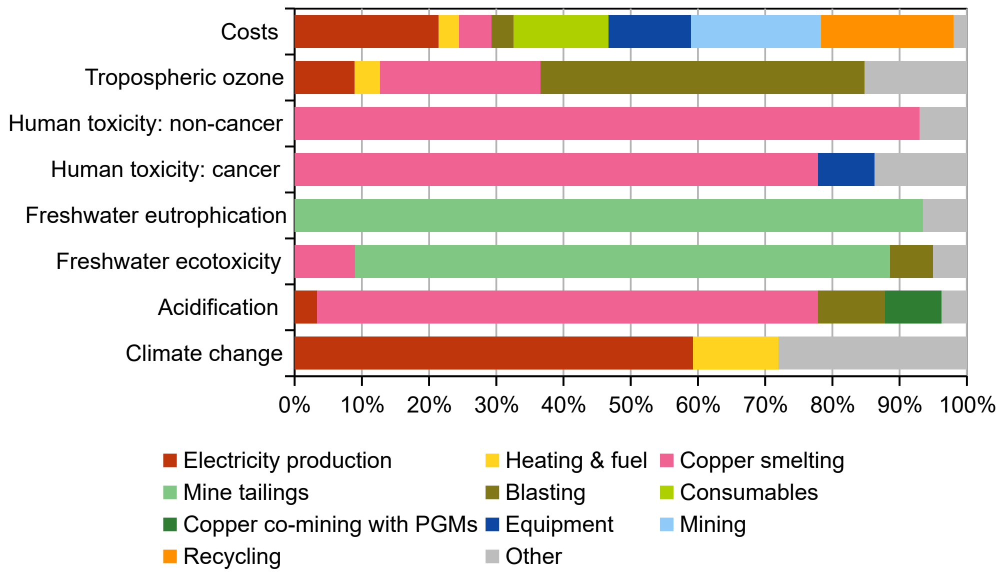

FIGURE 5.5: Contribution analysis of environmental impacts and costs of copper production. PGMs: platinum group metals.

5.5 Discussion

5.5.1 Limitations

Like cost-based learning, environmental learning curves are subject to several limitations, most of which apply to both. Both projections are sensitive to cumulative production estimates (Junginger et al., 2008) and to what is defined as the first industrial plant or unit. These aspects are important for the temporal pinpointing of future environmental impacts. To avoid double counting, studies should specify if economies of scale are included in the scope.

Learning is a multi-scale phenomenon, that takes place at the level of individual workers, teams, organizations, sectors, and society as a whole. This research focused on learning at a sector level, while encompassing learning on lower levels. Our approach does not account for knowledge spillovers that emerge at societal level (Clarke et al., 2008). To study this assimilation of technologies developed in other sectors, an integrated, economy-wide model would be required.

5.5.2 Methodological contributions

Bergesen & Suh (2016) and Thomassen et al. (2020) postulated that technological change is the central driver for both costs and emissions. Our approach, based on reviewed literature, emphasizes the guiding role of incentives for organizational and technological change. This conceptualization enables a structured analysis of environmental learning, decoupled from cost trends.

Our approach takes a neutral perspective on learning that is very suitable for explorative or predictive scenarios. It acknowledges that impacts could either increase or decrease due to learning, and it also covers unintentional effects on impacts. In contrast, eco-innovation literature focusses on drivers and incentives for impact reduction specifically, reflecting a normative perspective. Depending on the research aim, learning curves are one of many scenario generation methods (Arvidsson et al., 2018; Cho & Daim, 2013). If a technology assessment revealed potential environmental impact reductions, the proposed analysis helps to indicate the likelihood of realizing those reductions and the expected rate of change. Therefore, we support the recommendation to combine a bottom-up and top-down approach (Santhakumar et al., 2021; Thomassen et al., 2020) for technology scenarios and roadmaps.

5.5.3 Implications

Understanding the ubiquity of cost-based learning curves can accelerate learning. Cost incentives are predictable, unavoidable, and relatively constant. Moreover, costs can be translated to KPIs that are supported by managers and understood by investors and operators. Environmental learning will be stimulated if more stakeholders would reward environmental performance and would make long-term commitments. Currently, the incentives involved in environmental learning appear less constant. Consequently, both emerging and existing industries can quickly alleviate environmental pressures once appropriate incentives are implemented.

There is a selection bias in empirical emission data for some pollutants. Organizations that report their emissions are more inclined to reduce emissions (Christensen et al., 2017; Downar et al., 2021). Monitoring and disclosure are intermediate steps between awareness and action. Concurrently, this implies that reporting can support environmental learning.

5.5.4 Recommendations for future research

Future research on environmental learning in LCA could benefit from integrating insights from eco-innovation studies, which provide valuable quantitative evidence. However, it is challenging to apply the findings of these studies in LCA, as eco-innovation outcomes are reported in binary terms (Horbach et al., 2012), as absolute numbers (Wang et al., 2018) or per economic output (as in EU assessments (Al-Ajlani et al., 2022; Kemp et al., 2019)). To strengthen the connection, eco-innovation outcomes should be reported as relative impacts (e.g. energy use per functional unit), preferably per (sub)sector. Note that LCAs define the functional unit precisely, whereas eco-innovation studies include more diverse or variable products. Greater synergies are therefore expected for (sub)sectors with a more uniform product, such as paper or asphalt.

Besides the studies cited in §5.2.5, additional evidence for environmental learning may be obtained. Future research may expand the evidence by re-evaluating existing datasets from a learning curve perspective. For example, environmental learning of agricultural products can be studied using FAO statistics on fertilizer use efficiency. Manufacturing companies and industry associations may apply our procedure to their historical data on process efficiencies or emissions. Only if more data becomes available, the uncertainties for extrapolation will be reduced to an acceptable level. Moreover, empirical research can help to refine the approach and possibly identify more variables that influence environmental learning. Future research could explore learning in the context of services. Service-providing activities have greater flexibility in terms of input and functional output (Torugsa et al., 2018), adding complexity to the analysis. This extension is relevant because many products are ultimately used to provide a service.

5.6 Conclusion

Learning curves have been applied extensively as empirical trends to extrapolate costs. This study investigated the fundamental mechanisms of learning, to develop an approach for environmental learning in LCA. Technologies and production processes often evolve in response to incentives created by stakeholder pressures. Therefore, learning affects environmental impacts if these impacts are interlinked with prevailing business performance indicators.

A few studies have examined the influence of learning on resource use and emissions trends. These studies have primarily found reduced energy consumption over time, suggesting that environmental impact reduction is more likely for energy-intensive emerging technologies. Other impact categories remain less explored. Building upon reviewed theories, we proposed a procedure to anticipate environmental learning effects. This procedure complements guidelines for ex-ante LCA in two ways: by addressing the industrial development phase, and by providing a temporal outlook. These insights support decision-making regarding emerging technologies by informing scenarios, roadmaps, and investment strategies.

Data availability

The data that supports the findings of this study are available in the supporting information of this article, which may be found in the online version of the article at the publisher's website. The data that support the findings of § 5.4.2 are available from Ecoinvent. Restrictions apply to the availability of these data, which can be accessed at www.ecoinvent.org.

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