**Using patents to support prospective life cycle assessment: opportunities and limitations**

Christian Spreafico1, Nils Thonemann2, Massimo Pizzol3, Rickard Arvidsson4, Bernhard Steubing2, Stefano Cucurachi2, Giuseppe Cardellini5, Matteo Spreafico6

*1University of Bergamo, Department of Management, Information and Production Engineering*

*2Leiden University, Department of Industrial Ecology  
3Aalborg University, Department of Sustainability and Planning*

*4Chalmers University of Technology, Environmental Systems Analysis*

*5VITO-EnergyVille*

*6University of Bergamo, Research and Technology Transfer Office*

# Abstract

**Purpose**

Some prospective life cycle assessment (LCA) studies obtain information from patents, albeit without exploiting their full potential. The objective of this study is to show which data and information can be retrieved from patents to inform practitioners when conducting a prospective LCA of an emerging technology.

**Methods**

Potential matches between prospective LCA challenges and patent analysis techniques, as well as the opportunities and limitations, have been collected through literature review and theoretical reasoning.

**Results and discussion**

The analyses of patent geographical jurisdiction, publication trend, maintenance costs, citations and infringement can be used to define geographical and temporal scope and to select technology alternatives. Function(s), quantitative data, and information about scale-up and technological trends can be extracted from patents and used to predict function(s) of the new technology, fill the prospective life cycle inventory (pLCI), and choose existing LCI datasets. However, limitations of patents that could prevent their use in prospective LCA are: (i) some information can be intentionally distorted to hinder competitors; (ii) patent bibliometrics indicators to evaluate the future success of patented technology on the market can be overstated by patents of well-known owners that receive more citations and infringements albeit with no greater chance of future development; (iii) patenting to block competitors rather than to develop a new technology; (iv) the lack of significance of certain data due to the too low TRL of the prototype from which they were obtained; (v) a less than rigorous data examination process; (vi) patents are not very helpful to quantify emissions.

**Conclusions**

We show how patents can be used to support prospective LCA when the assessment cannot count on the support of technology experts. We highlight how it is necessary to pay more attention, compared to the current practice in prospective LCA, to the peculiarities of patent prose and the legal and strategic use of patents by companies.

# Keywords

Life Cycle Assessment, Prospective LCA; Patent analysis; Prospective LCI; Technological forecasting

# Introduction

Conducting a prospective LCA (LCA) involves assessing the potential environmental impacts of a product or process at a future point in time relative to when the study is conducted, often before the product or process is fully developed or implemented (Arvidsson et al., 2023). Compared to standard LCA, the information about the product system is lower in prospective LCA and the number of approximations and estimates in data collection is higher, especially when modelling technologies with a low level of maturity (Hetherington et al., 2014). To assess the environmental impacts of technologies in the future, prospective LCA makes use of information extracted from different sources such as scientific publications, unpublished laboratory results, simulations and expert interviews (Arvidsson et al., 2018). Patents have also been considered due to their ability to reveal information about immature technologies that could be both technically and economically viable for large-scale production (Jaffe and Trajtenberg, 2002). For this reason, patents are particularly useful for supporting the evaluation of the future impacts of new technologies that are still in the R&D phase by anticipating mature technology conditions (Arvidsson et al., 2018; Thonemann et al., 2020).

Despite being used in some prospective LCA studies, the potential of patents has not been fully exploited compared to other types of studies dealing with technological forecasting (e.g., Parteka and Kordalska, 2023; Yuan and Cai, 2021; Daim et al., 2020). García-Cruz et al. (2022), Berger et al., (2022); Castillo et al. (2023) considered no more than 10 patents without reporting search criteria. Morales-Gonzalez et al. (2019) and Raugei and Winfield (2019) conducted a systematic and manual analysis of patent text to extract data for the foreground inventory. Karp et al. (2022) and Haase et al. (2022) explicitly reported the search query and considered more than 100 patents, from which they extrapolated trends to support technological forecasting. Spreafico et al. (2023) suggested selecting granted and updated patents of technologies that perform the same function as the analysed product and extracting from them quantitative information supported by experimental tests to support prospective LCA of immature technologies.

In addition, studies about patent data quality reveal the following elements that were not considered in patent-based prospective LCA studies. Patent texts are often deliberately written with strategic ambiguity, serving the dual purpose of securing legal protection while concealing key information from competitors (de la Fuente et al., 2020). Consequently, it can be beneficial to involve the expertise of a legal professional in the interpretation of patent texts (Ashtor, 2022). Misspellings in patent texts, whether intentionally introduced by specific patent attorneys to obscure content from competitors or arising from mistranslations, can impact the precision and recall of patent searches. Consequently, it is crucial to conduct patent searches with awareness of this potential influence on accuracy (Russo et al., 2023). The relevance of a patent can change depending on the application field and geographical area (Boeing and Mueller, 2019). The patent analysis techniques, even the advanced ones based on deep learning, suffer from some limitations in information retrieval and text mining, such as the cold start problem during the learning phase of the neural network (Krestel et al., 2021).

The existing literature currently lacks a specific analysis regarding which patent analysis techniques are suitable for supporting prospective LCA, considering factors such as the maturity level of the analysed technology and the various operational steps involved in the analysis (Sandén and Hillman, 2011). Retrieving information on R&D efforts from patents and conducting patent bibliometrics analysis for predicting market trends necessitate complementary approaches, tools, time and resource commitments.

The research gap addressed by this study is how patent analysis can support prospective LCA. The study thus aims to identify those patent analysis techniques and applications suitable to support prospective LCA, as well as their limitations.

# Materials and methods

To achieve the aim of the study, the most suitable patent analysis techniques to support prospective LCA have been identified in a literature review. Each patent analysis technique was then manually associated with one or more challenges in the prospective LCA field that the technique can help overcome. In addition, the limitations of each technique in supporting the prospective LCA challenges were also identified based on the level of detail and the relevance of the extracted information.

## Patent analysis techniques review

Many patent analysis techniques have been proposed in the literature, which implements different methods and tools to fulfil various purposes (Abbas et al., 2014; Zhang et al., 2021; Chen et al., 2020). A literature review has been conducted to compile an exhaustive list of commonly used patent analysis techniques to determine whether they can address specific challenges in prospective LCA. To address the heterogeneity of the jargon with which patent techniques are defined (Abbas et al., 2014), the review was carried out using the following generic keywords: patent analysis, patent search, patent retrieval, patent analytics, and patent mining. The search query was launched in the Google Scholar and Scopus databases to collect as many sources as possible since they are disseminated in different fields, e.g., legal, technological forecasting, marketing, research and development. To increase the relevance of the analysis, only reviews and articles published in international peer-reviewed journals were considered. Further reviews and articles have been iteratively retrieved from the collected sources, following the snowballing approach (Jalali and Wohlin, 2012).

For each of the most common patent analysis techniques reviewed, the following information has been collected:

* What information can the technique extract from a patent?
* How does the technique extract this information, e.g., through a theoretical method or implementing a tool?
* What limitations does the technique suffer from, e.g. in terms of the level of detail of the extracted information?

## Considered prospective LCA challenges

In this section, the prospective LCA challenges considered in this study are introduced and related to the four main steps of the LCA framework: goal and scope definition, inventory analysis, and interpretation[[1]](#footnote-1).

The definition of the goal and scope in an LCA study identifies its purpose and outlines the boundaries and details of the product system under study. Common goals in prospective LCA involve assessing the environmental impacts of a currently immature technology at a future mature state. Accordingly, the geographic and temporal scope of the assessment should be defined consistently with the market and the future point in time when the technology will reach maturity (van der Giesen, 2020). The definition of the functional unit can be challenging in prospective LCA, especially for technologies with a currently low level of maturity (Hetherington et al., 2014; van der Giesen, 2020). Challenges arise also when attempting to select relevant technology alternatives for comparison with currently mature technologies (Arvidsson et al., 2023).

In prospective LCA, the availability of LCI data for technologies at low TRLs is limited. This is due to, among others, the lack of historical and database data on novel materials and processes, as well as confidentiality issues related to new products and industrial processes. The latter makes it challenging to gather primary data, while the former renders it difficult to find secondary data (Moni et al., 2020). When available, lab-scale data can help overcome LCI data shortage, but such data might still be notably different from that of industrial processes. To make lab-scale data relevant for future states, they need to be projected to that of a mature product by upscaling (Tsoy et al., 2020). Such upscaling needs to rely on experience for professionals, however, the significance of support decreases when new technologies are considered (Piccinno et al., 2016). Another challenge pertains to the selection of relevant (secondary) datasets from LCA databases, which can sometimes be used as proxies for the future (Arvidsson et al., 2018).

The interpretation should include a sensitivity analysis to account for parameter uncertainty, which in prospective LCA also depends on the future development of the technology under study (Thonemann et al., 2020).

Table 1 reports the considered prospective LCA challenges.

*Table 1: Considered prospective LCA challenges.*

|  |  |
| --- | --- |
| **LCA phase** | **Prospective LCA challenge** |
| **Goal and scope definition** | **Define the geographical scope.** How to identify the market of the immature technology at a mature state? |
| **Define the temporal scope.** How to identify the time when the immature technology reaches maturity? |
| **Identify the function of a new technology.** How to predict the future functions of the immature technology at a mature state? |
| **Select technology alternatives.** Which parts of the life cycle of the product system could change in the future? |
| **Inventory analysis** | **Estimate prospective inventory data.** How to make up for the lack of primary data on immature technologies? |
| **Technology scale-up.** How to perform upscaling of new technologies? |
| **Select LCA datasets.** How to select relevant LCA datasets for an immature technology when supporting information are missing? |
| **Interpretation** | **Uncertainty analysis.** How to account for uncertainty due to future development of the considered technology? |

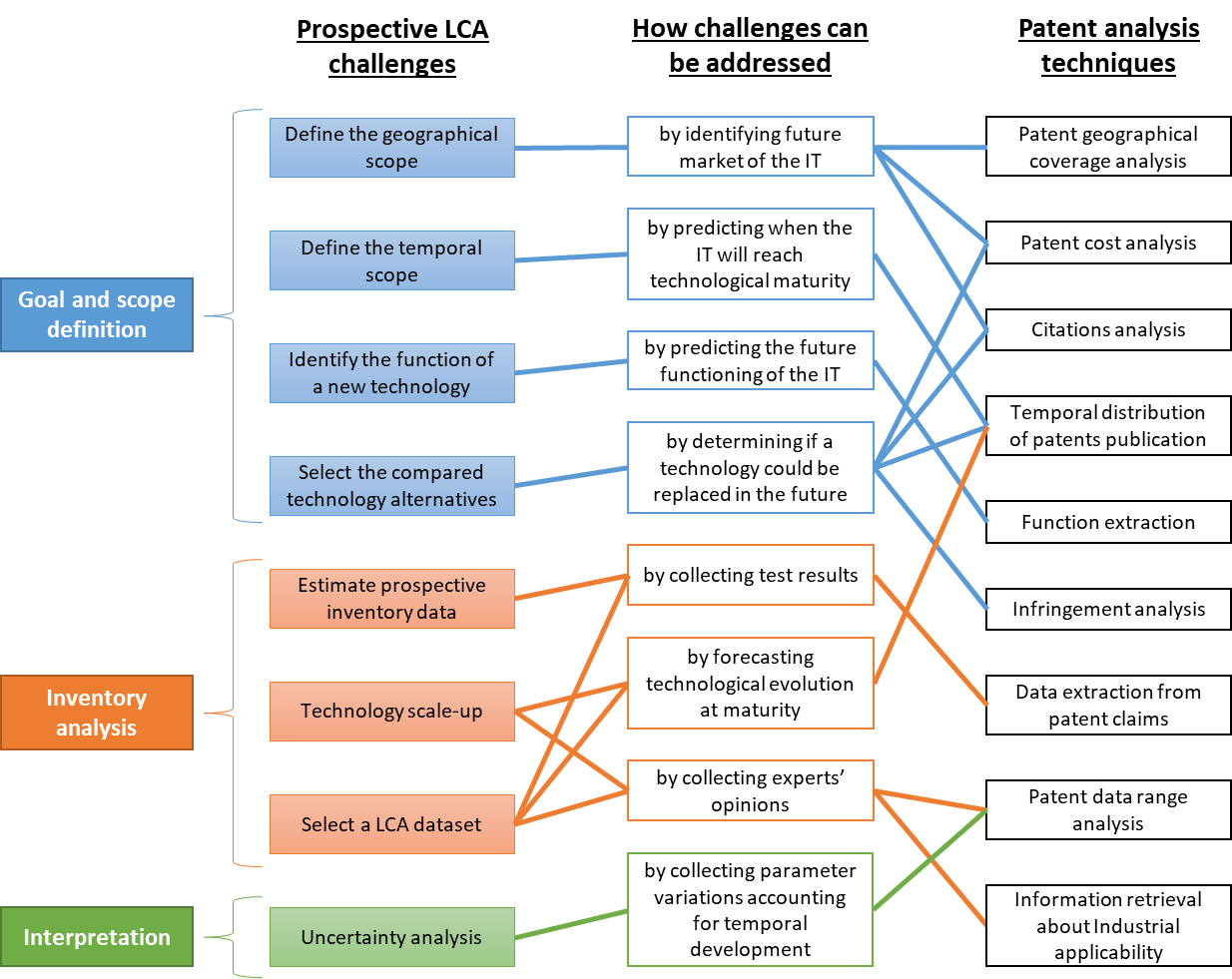
# Results

Table 2 lists the patent analysis techniques identified in the literature review. Each technique has been automatized for analysing many patents but can also be used to extract information manually from a single patent.

*Table 2: Considered patent analysis techniques.*

|  |  |
| --- | --- |
| **Overarching patent analysis techniques** | **Specific patent analysis techniques** |
| **Patent bibliographic analysis** retrieves information about patent owners, maintenance costs and geographical coverage | **Patent cost[[2]](#footnote-2) analysis** monitors who invests and how much to maintain a patent “alive”, which is correlated with the interest in its future development (Russo et al., 2023) |
| **Patent geographical coverage[[3]](#footnote-3) analysis** determines in which country the patent has been filed and is maintained “alive”, indicating potential future markets (Yuan and Li, 2021) |
| **Patent bibliometrics** uses the same indicators as bibliometrics of scientific documents to analyse patent trends | **Temporal distribution of patent publication** is used to evaluate the diffusion over time of the patent activity (Yuan and Cai, 2021) |
| **Citations analysis** is used to evaluate the popularity of a patent according to the citations received, typically by other patents (Kim et al., 2016) |
| **Patent mining** is used to collect qualitative and quantitative information from patent texts | **Function extraction** from the patent is used to characterise the described technology about its functioning (Liu et al., 2020) |
| **Information retrieval about industrial applicability** is used to understand how the patent owner intends to manufacture the claimed technology (Chen et al., 2017) |
| **Collection of different information from different parts[[4]](#footnote-4) of the patent** is used to discriminate information about their purpose in the patent, e.g., claim an experimental datum or provide a future prediction (Chen et al., 2017) |
| **Patent data extraction** is used to retrieve numerical values for certain parameters of the described technologies (Butriy, 2016) |
| **Patent data range[[5]](#footnote-5) analysis** is used to discriminate the part of a range of parameter values deriving from experiments or measurements from that are used to increase the legal protection of the patent for future developments (Butriy, 2016) |
|
| **Additional documents[[6]](#footnote-6) analysis** is used to evaluate patent quality | **Infringement analysis** is used to evaluate whether and when a patent has been accused of plagiarising other patents (Pénin, 2012) |

The opportunities to address each of the considered prospective LCA challenges applying the identified patent analysis techniques are summarised in Figure 1 and explained in the remainder of this section.



*Figure 1: Identified patent analysis techniques to support prospective LCA and reasons (how), where IT = immature technology.*

## Goal and scope definition in prospective LCA

### Define the geographical scope

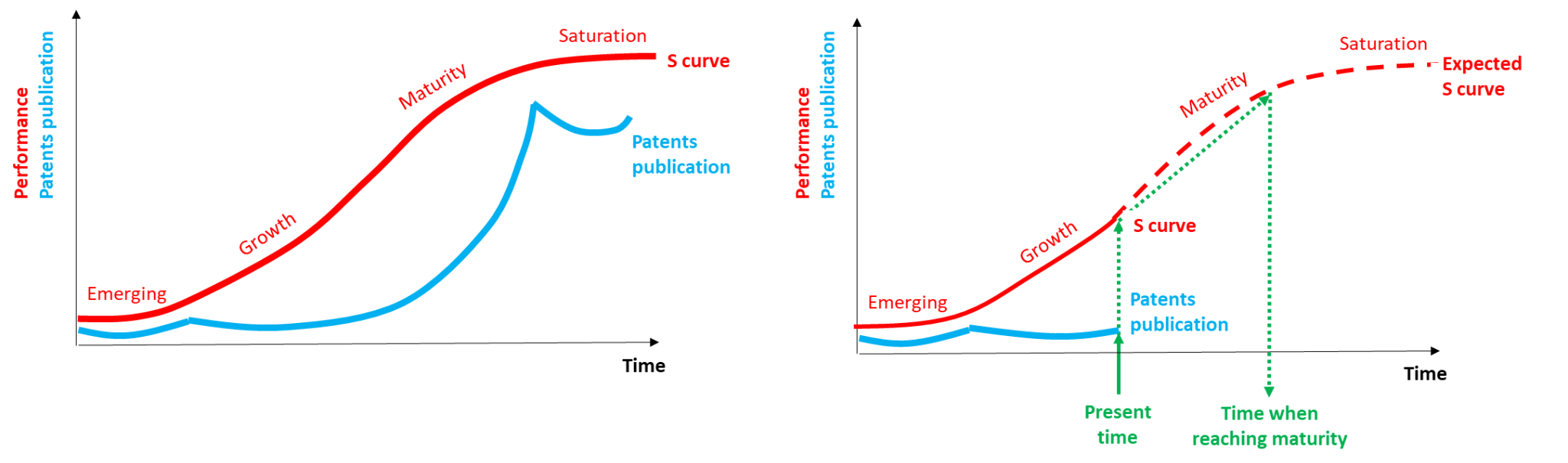
To define the geographical scope, i.e., the market in which the immature technology will be commercialised and used when it reaches maturity, patent geographical coverage analysis can be used. This is based on the rationale that the selected filing countries are correlated to the most attractive markets for the patented technology (Yuan and Li, 2021) since a patent provides a monopoly and allows the full economic potential of the patent to be exploited (Cuellar et al., 2022). When more countries are claimed by a patent, it is possible to discern those having the highest interest to the patent owner through maintenance costs analysis (Karkinsky and Riedel, 2012). The analysis of the geographical distribution of patent citers can also be useful to understand in which countries the patented technology is of greatest interest (Thompson, 2016).

However, using patent geographical coverage to define geographical scope has two limitations. The extent of geographical coverage granted by a patent can vary, as the patent owner may choose to maintain different extensions of the patent over an extended period or expand the patent into new countries at a later date. Such changes are due to changes in the development strategy of the patented technology or if the patent is reassigned (Caviggioli et al., 2020). In addition, some industries use the blocking patent strategy, by filing a patent in a certain country only to prevent competitors from developing the technology (Torrisi et al., 2016).

### Define the temporal scope

To identify the moment in time when the analysed immature technology will reach maturity, the analysis of the temporal distribution of patent publication has already been employed, although outside the domain of prospective LCA (Phan and Daim, 2013; Yuan and Cai, 2021; Adamuthe and Thampi, 2019; Mao et al., 2017; Ernst, 1997). These approaches identified the S curve about performance and the patent publication curve for a number of technologies when they reached the saturation phase. They demonstrated that similar technologies have similar curves and they interpolated them for a certain technological class (see Figure 2 left). They hypothesised that a new technology that is in an emerging or growth phase therefore has curves similar to those of a different class of similar technologies. Therefore, on the basis of this hypothesis it is possible to reconstruct the missing traits of the curves of a new technology (see Figure 2 right) through the comparison with the curves of a similar technology class (Figure 2 left).

To apply these approaches to identify the time of the study, the prospective LCA practitioner chooses a reference correlation between the S curve and the patent publication curve for the technology under study. The practitioner then analyses the patent publication curve of the technology at present and estimates the future time when reaching maturity (i.e., a certain performance) through the correlation with the S curve, travelling along the predicted trait of the S curve till the mature state (see Figure 2 right).



*Figure 2: (left) Comparison between publication trend and S curve (adapted from Ernst, 1997) and (right) its use to predict when the immature technology will reach maturity (time of the study).*

The main limitation of this approach is the hypothesis that in a new technology, the S curve could be the same as similar technologies having reached the saturation phase. In some cases, this did not occur due to unexpected changes in industrial strategies, and environmental and legislative scenarios (Phan and Daim, 2013; Yuan and Cai, 2021; Adamuthe and Thampi, 2019; Mao et al., 2017). The same authors, therefore, suggest the integration of other predictions relating to these aspects to validate the use of such approaches. In addition, the significance of the curves for a certain class of technology can be questioned based on the low number of analysed technologies.

### Identify the function of a new technology

To predict the future functioning of an immature technology, the prospective LCA practitioner can apply the techniques of function extraction (e.g., Liu et al., 2020, Fantoni et al., 2013) that automatically extracts the functions performed by similar technologies claimed in a selected patent pool. These techniques analyse a patent text and identify the technology as well as the functions performed through syntactic analysis where the technology is the so-called “subject” and the functions are the verbal predicates associated with the “subject”. In addition, the same techniques can classify the many extracted functional verbs into more generic pre-defined functions, e.g., “Transport” and “Transmit” as “Transfer” (Kitamura et al., 2004). This can help the prospective LCA practitioner to save time when analysing many patents related to the considered technology to check for any new functions to be considered in the goal and scope definition.

The efficiency of automatic function extraction may be limited by the ambiguity in defining the functions in patents. For instance, in Liu et al., (2020) the function is defined as the objective for which the patented technology is designed, while Fantoni et al., (2013) define the function as the working principle and operating parameters. Hence, it is crucial to properly define the functions to be extracted based on the prospective LCA goal and, accordingly, choose the most suitable tool to extract them from patents. Since it is reasonable to presume that different tools may retrieve different functions or present the same functions articulated in different forms, a manual interpretation and check might always be needed. Another limitation concerns the linguistic ambiguities arising from the automatic analysis of Chinese patents, where sentences representing different meanings may appear to have the same syntactic structure, rendering analysis results unreliable (Sun et al., 2022). The result is that if a sentence contains two technologies and a function performed by only one, the function is attributed to the wrong technology.

### Select the compared technology alternatives

To identify the most promising technology for modelling the system in the future time among different alternatives, the prospective LCA practitioner can analyse and compare some parameters of the patents related to each compared alternative. As a result, the most promising technology should have:

* The greatest increases in patenting and patent investment during the past period reflected an increased interest from developer industries (Kogan et al., 2017; Choi et al., 2020; Spreafico et al., 2021). Temporal distribution of patent publication and patent cost analyses can be used for this purpose.
* The highest number of citations received by other patents is an indication of the interest from other industries (Kim et al., 2016). For this purpose, the automatic citation analysis available in the common patent databases can be used. In addition, deep learning approaches have been used to predict the number of future citations (Chen et al., 2020) that a patent may receive. This broadens the scope of these analyses, offering prospective insights across a more extended time horizon.
* The highest number of infringements received by other industries. This is because an industry seeking to develop a technology is more inclined to contest the patents of competitors aiming to develop the same technology (Pénin, 2012). For this purpose, the infringement report can be analysed (Liu et al., 2018).

Patent publication and patent cost analysis cannot risk underestimating the future diffusion of a mature technology having declining patenting, albeit with good estimates of other types (e.g., historical market trend) for the future diffusion (Russo et al., 2023).

The limitation of the analysis of citations and infringement analyses concerns the fame of the patent owner, which can distort the comparison, promoting their patented technologies as more promising. Indeed, patents of well-known owners (e.g., big firms) receive more citations and infringements than those of less known owners (e.g., innovative start-ups) without necessarily claiming technologies that are more likely to be developed in the future (Breitzman and Mogee, 2002; Brauneis and Heald, 2011). This is because the patents of famous owners are more widespread and well-known.

## Inventory analysis

### Estimate prospective inventory data

Primary data about immature technologies can be extracted from patents that typically report laboratory-scale results to verify the claims about the patented technology. To collect these data from a patent, it is suggested that they are extracted from the claims rather than from other parts of the patent to increase their accuracy since the claims are compulsorily subject to the examiner's judgement (Chen et al., 2017). In the claims, only information that allows the patented technology to be qualified as truly innovative and original are reported and they have legal value in patent litigation. In the other parts of the patent, additional information is also provided about the state of the art or assumptions and possible future developments, which are often not justified by experimental tests, contrary to the data in the claims.

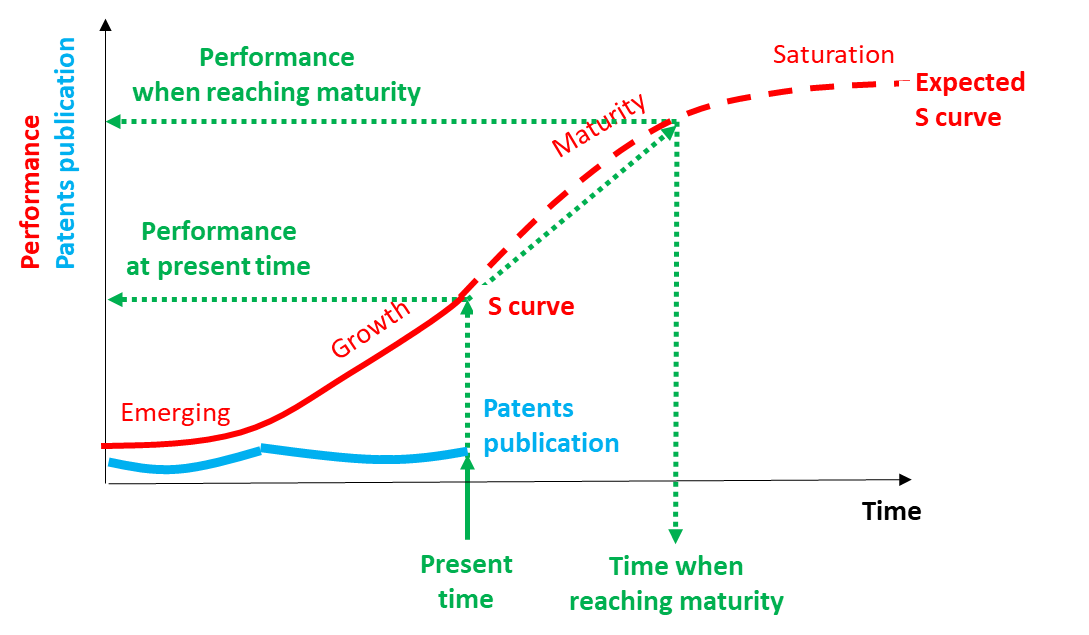
To evaluate the data reliability, the prospective LCA practitioner can also analyse the patent description looking for supporting information (Spreafico et al., 2023). To grant the patent, the examiner requires the data present in the claims to be supported by experimental test results accurately described in the patent description. The adherence of the experimental tests to certain protocols declared in the patent and any references to scientific publications that justify the laboratory scale results can be evaluated.

The main limitation of using numerical data from patents is that the TRL of the tested technologies can be significantly lower than those tested in scientific publications (e.g., Hussin and Aroua, 2020). This is because the purpose of the patent is to protect technical knowledge about the future development of a product rather than to scientifically certify the feasibility of what is claimed.

### Technology scale-up

The lab-scale data collected can be scaled up either by forecasting the technological evolution at maturity or by collecting experts’ opinions.

The analysis of the temporal distribution of patent publications can be used to support the modelling of a scaled-up version of the technology by forecasting its technological evolution. Using the same approaches described in Section 3.1.2, the performance of a given parameter at technological maturity can be predicted following the expected S curve, and looking at the y-axis instead of the x-axis as before (Figure 3).



*Figure 3: Comparison of the temporal distribution of the patent publication and the S curve to support scale-up by predicting the performance of a parameter at technological maturity (adapted from Mao et al., 2017).*

Since the following approach is the same, the limitations are those previously described in Section 3.1.2.

Experts’ opinions about data scale-up can be collected from patents by using the following patent analysis techniques.

* To retrieve the quantitative information that can help to scale up lab-scale data, data range analysis can be used. For the same parameter, the data range extracted from the patent claim can be compared with the data range extracted from the description, which results from experimental tests. Data range analysis helps to distinguish the portion of the data range associated with laboratory test results from the other portion used to broaden the legal protection of the claim. For example, the patent CN114178538 (Xu et al., 2021) about a rotary plasma atomiser for the production of titanium powder, reports in its claims a rotation of the electrode between 30000 and 35000 rpm. In the description, on the contrary, it only reports experimental tests referring to a rotation of 35000 rpm. One can therefore assume the intention of the patent owner to achieve a lower rotation speed at technological maturity (i.e., 30000 rpm).
* The industrial relevance of the patented technology can be analysed by collecting information about up-scaling (Sun et al., 2022; Ai et al., 2022). This information, provided in the description of the patent, references experimental results from other patents or scientific publications about similar technologies that have been scaled up to the industrial level (Chen et al., 2017). For instance, patent EP3666754 (Ma et al., 2018) describes the scale-up of the reaction time of the claimed chemical process by referring to a similar technology described in another patent, i.e., US8088942 (Corpart et al., 2006): "... due to the inevitable amplification effect, the industrial scale reaction time is 2-180 times of the laboratory scale”.

However, data ranges do not always represent results to be used in the prospective LCA because they do not exclusively report data acquired from experiments but are also used by the patent owner to claim a certain development perspective to secure margins against competitors (Butriy, 2016). In the case of an asymmetric range from the claimed value, the closest limit to this value is usually obtained from an experimental result. The farthest limit to the claimed value is assumed to be a prospective result of the technology at maturity. This was done for instance in patent CN114178538.

Information about industrial applicability can be intentionally manipulated by patent attorneys to conceal details from competitors (de la Fuente et al., 2020). Therefore, when dealing with scale-up information, it becomes essential to carefully verify the accuracy of the data (Robson, 2001; Maynard et al., 1979). Moreover, patent attorneys frequently resort to industrial secrecy regarding some information about industrial applicability, especially in patents about industrial processes, making this information known only to the examiners through an additional document and not indicated in the text of the patent (Crass et al., 2019).

### Select an LCA dataset

The prospective LCA practitioner can use some information about a patent to select an LCA dataset about a manufacturing process from an LCA database. They are those about the industrial applicability of the claimed technology that, to pass the examination, can be justified by providing the details of manufacturing technology (Pozo, 2017). For instance, patent CN102517578 (Yang, 2011) about a dual-alloy cladding layer wear plate describes the manufacturing technology as follows “Mounting the glasses plate on a workbench with a rotating mechanism and performing laser cladding on an inner hole of the glasses plate by adopting iron-based alloy. [...] The laser cladding equipment adopts a Trumpf 6000-watt CO2 laser (with a wavelength of 10.6um)”. This information can be used to select the LCA dataset “laser machining, metal, with CO2-laser, 6000W power – RER Europe”, from Ecoinvent database version 3.9. This is because, in addition to the type of laser and power, this dataset explicitly refers to a machine produced by that manufacturer.

This technique can be limiting especially when the patented technology is very innovative and will take a long time to develop. In this case, the prescribed manufacturing technology, especially if existing for a long time, could change when the patented technology is produced (Domeij, 2000).

## Interpretation

### Uncertainty analysis

To evaluate the uncertainty about the future development of the considered technology, patent data range analysis can be exploited albeit with limitation in the scale-up (cf. Section 3.2.2.).

Table 3 reports the opportunities and limitations of using each patent analysis technique in addressing each of the identified prospective LCA challenges.

*Table 3: Identified patent analysis techniques to address prospective LCA challenges with the respective opportunities and limitations.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **LCA phase** | **Prospective LCA challenge** | **Patent analysis technique** | **Opportunities** | **Limitations** |
| Goal and scope definition | Define the geographical scope | Patent geographical coverage analysis  Patent costs analysis  Citations analysis | Collect future markets that industries have identified for immature technology | Patent geographical jurisdiction could change over time if the patent owner changes the development strategy of the claimed technology or if the patent is reassigned.  A patent can be filed in a certain country only to prevent competitors from developing the technology |
| Define the temporal scope | Temporal distribution of patents publication | Predict the maturity level of the immature technology according to the patents publication | Unexpected changes in industrial strategies, environmental and legislative scenarios could invalidate the prediction |
| Identify the function of a new technology | Function extraction | Understand the expected functions of technologies not yet on the market | Ambiguities in defining the concept of "function" as either a goal or a mode of operation  Linguistic and syntactic ambiguities in Chinese patents and automatic translations can invalidate the automatic function extraction |
| Select the compared technology alternatives | Temporal distribution of patents publication  Patent costs analysis | Compare the interest that industries have in developing different technology alternatives | Risk of underestimating the future diffusion of mature technologies with declining patent activity |
|  | Citations analysis  Infringement analysis | Compare the interest that industries have in different technology alternatives proposed by other industries | Patents of well-known owners can receive more citations and infringements albeit with no greater chance of future development |
| Inventory analysis | Estimate prospective inventory data | Data extraction from patent claims | Retrieve experimental results from the patent owner and examiner’s reviews | Lab-scale results in patents are obtained from technologies having lower TRL than those tested in scientific publications |
| Technology scale-up | Patent data range analysis | Collect quantitative estimations about technological scale-up from the patent owner | The data ranges include a portion of noise to conceal information from competitors |
| Temporal distribution of patent publication | Predict the technological scale-up when direct data are lacking | Unexpected changes in industrial strategies, and environmental and legislative scenarios could invalidate the prediction |
| Information retrieval about industrial applicability | Collect qualitative and quantitative estimations about how the industry developing the patented technology intends the technological scale-up | Information can be intentionally distorted ad hoc by patent attorneys to conceal information from competitors  Information about industrial applicability can be covered by industrial secrecy, especially in patents about industrial processes |
|
|
|
| Select an LCA dataset | Information retrieval about industrial applicability | Collect the manufacturing processes of the immature technology identified by the industry developing it | The manufacturing process and technologies suggested in the patent could change when the claimed technology will be produced |
| Interpretation | Uncertainty analysis | Patent data range analysis | Collect quantitative estimations about the uncertainty about scale-up that patent owners have | The data ranges include a portion of noise to conceal information from competitors |

# General patent limitations affecting prospective LCA

To maximise the effectiveness of the proposed patent analysis techniques to address prospective LCA challenges, it is necessary to mitigate the following general patent limitations in the context of prospective LCA.

## Searching a patent

A patent is often written to avoid giving information to competitors. Therefore, patent attorneys use as broad a vocabulary as possible within the limitations of what is allowed by a patent examiner. The text may therefore be full of synonyms, generic or little-used terms and misspellings (Russo et al., 2022). In addition, machine translations can introduce additional lexical and syntactic ambiguities (Büttner et al., 2022).

All these aspects negatively influence the effectiveness of keyword patent searching. To make up for this shortcoming, patent research can be supported by some techniques. Text mining tools based on artificial intelligence can interpret an incorrectly formulated word thanks to context analysis (e.g., Hu et al., 2020). Dictionaries such as Wordnet can be integrated for semantic query expansion (Sarica et al., 2020). Query reduction techniques reduce and eliminate keywords using patent class searching (Shalaby and Zadrozny, 2019). This type of research, already used in some prospective LCA studies (e.g., Karp et al., 2022), is limited because of the high degree of abstraction with which the classes are defined concerning technological aspects and classification inaccuracies (Montecchi et al., 2013).

If, on the other hand, the prospective LCA practitioner wants to search for a patent for an innovative technology that is not known and cannot be described at the structural level, the structure-based search cannot be used. In this case, function-based search can be exploited, where keywords are the functions expected to be performed by the technology (Liu et al., 2020; Spreafico et al., 2023). In this case, text mining with syntactic analysis is supportive, understanding whether the verb expressing the function refers to the subject (i.e., the technology) performing it (Teng et al., 2024).

## Checking the quality of a patent

Having identified the patent sought, its quality must be carefully analysed regarding its usefulness in a prospective LCA context. Considering an unworkable patent in a prospective LCA study is not only useless but also misleading as it offers an opposite perspective to what will likely occur in the future. Indeed, most patents are not realised due to the 'valley of death', i.e., the situation where a new technology fails to succeed (Pizzol and Andersen, 2022). Certain patents are filed without an interest in developing them because some governments encourage R&D by counting patents among other key performance indicators to allocate subsidies to companies (Bao and Lu, 2020).

There are some strategies to select relevant patents with development potential, so it can be useful support to a prospective LCA.

The prospective LCA practitioner can analyse some indirect indicators to evaluate the quality of the patent for the prospective LCA, i.e., its usefulness for predicting the development of a new product in the future and obtaining its description. The patent owner is an indication of the likelihood of patent development. A patent by a start-up is less likely to end up in the ‘valley of death’ than one from a larger company (Pizzol and Andersen, 2022). The payment of patent maintenance fees can imply an interest on the part of the patent owner in developing that patent (De Rassenfosse and Jaffe, 2018). From the joint analysis of the patent text and the company situation (e.g., interviews), it is possible to understand what is the level of development of the claimed technology, e.g., a patent that has already been tested (Audretsch et al., 2012). The inclusion of favourable judgments provided by the examiner in the search report is an indication of patent relevance (Burke and Reitzig, 2007). However, search report analysis for selecting patent sources is subject to some limitations (EPO, 2023). The patent examination process differs from a scientific review, as it involves a more rigorous evaluation of novelty, originality, and industrial applicability of the claimed technology rather than how the experimental tests are conducted (Lee, 2021). No peer review is conducted, although the examiner has the option to reach out to an expert at their discretion. In addition, the severity of patent examination may vary across technological sectors, influenced by distinct evaluation procedures and varying percentages of infringement and allegations (Cockburn et al., 2003). Consequently, patent owners in specific application fields tend to submit patents of lower quality and exercise the blocking patent strategy (Torrisi et al., 2016).

## Where to retrieve data from patents

Many of the most popular patent databases have long allowed patents to be collected and semi-automatically extracted from them much of the information that has been described in this study (Burhan and Jain, 2012). However, not all databases are freely available or allow us to process information as required.

To support the prospective LCA practitioner in collecting and analysing patents a selection and comparison of patent databases have been reported in Table 4. Those presented are the most diffused patent databases with free access and indexing of all patents worldwide. The comparison considers the ability of each patent database to access the information presented in this study.

*Table 4: Comparison of the selected patent databases.*

|  |  |  |  |
| --- | --- | --- | --- |
| **Patent database features** | **Espacenet**  **(owned by European Patent Office)** | **Google patents** | **PatentScope**  **(owned by World Patent Organization)** |
| Web link | [Worldwide.espacenet.com](https://worldwide.espacenet.com/), Register.epo.org | [patents.google.com](https://patents.google.com/) | Patentscope.wipo.int |
| Retrieve patent bibliographic data: publication date and country, patent owner name | Yes | Yes | Yes |
| Retrieve received citations | Yes | Yes | No |
| Retrieve maintenance costs | Yes | Yes | Yes |
| Access patent text | Partially\* | Yes | Yes |
| Access search report | Yes | No | Yes |
| Retrieve the number of infringements | Yes | Yes | Yes |
| Access infringement report | Yes | No | Yes |
| Generate temporal and geographical distribution of patents | Yes (on payment) | No | No |

\* Only for patents retrieved from the databases of some countries (e.g., the Italian Patent Office Database).

# Conclusions

This study identified matches between prospective LCA challenges and patent analysis techniques through a literature review and theoretical reasoning, analysing opportunities and limitations. As a result, patents are considered valuable sources to support different prospective LCA challenges for which they have not yet been considered. In this regard, it has been explained which information a prospective LCA practitioner should extract from patents in what manner and with which techniques. The information is derived from patent bibliographic data (e.g., publication date and country, patent owner name), from the patent content and the comparison of multiple patents (e.g., publication trend).

The collected opportunities for using patents to support prospective LCA are the identification of future markets; the prediction of the time when the technology will research maturity; the identification of the functions of technologies not yet on the market; the monitoring of the interest of industries in patenting or patented new technologies; the collection of experimental data and data scale-up; the identification of manufacturing processes and technologies for the immature technology.

On the other hand, the collected limitations are the industrial strategy behind patenting in certain countries which distorts market identification; ambiguities in patent text; the fame of the patent owner which distorts the bibliometric indicators on the fame of the patent; the low TRL of the tested technologies; the presence of distorted information to conceal information from competitors.

Thanks to the results of this study, we believe that a prospective LCA practitioner can autonomously analyse and use patents in a good or at least better way in a prospective LCA study. At the same time, we also believe that a deeper patent analysis, also carried out with specific tools and in collaboration with patent analysis experts, can find more results and fill some of the limitations.

The main limitation of this work lies in the theoretical level at which the potential matches were obtained. Consequently, this work can be seen more as a first investigation of the potential of patents in prospective LCA. For this reason, possible future developments could involve the testing of our recommendations in case studies to provide validations and new practical insights.

# References

Abbas, A., Zhang, L., & Khan, S. U. (2014). A literature review on the state-of-the-art in patent analysis. World Patent Information, 37, 3-13.

Adamuthe, A. C., & Thampi, G. T. (2019). Technology forecasting: A case study of computational technologies. Technological forecasting and social change, 143, 181-189.

Adrianto, L. R., van der Hulst, M. K., Tokaya, J. P., Arvidsson, R., Blanco, C. F., Caldeira, C., ... & Hauck, M. (2021). How can LCA include prospective elements to assess emerging technologies and system transitions? The 76th LCA Discussion Forum on Life Cycle Assessment, 19 November 2020. The International Journal of Life Cycle Assessment, 26(8), 1541-1544.

Arvidsson, R., Svanström, M., Sandén, B. A., Thonemann, N., Steubing, B., & Cucurachi, S. (2023). Terminology for future-oriented life cycle assessment: review and recommendations. The International Journal of Life Cycle Assessment, 1-7.

Arvidsson, R., Tillman, A. M., Sandén, B. A., Janssen, M., Nordelöf, A., Kushnir, D., & Molander, S. (2018). Environmental assessment of emerging technologies: recommendations for prospective LCA. Journal of Industrial Ecology, 22(6), 1286-1294.

Ashtor, J. H. (2022). Modeling patent clarity. Research Policy, 51(2), 104415.

Audretsch, D. B., Bönte, W., & Mahagaonkar, P. (2012). Financial signaling by innovative nascent ventures: The relevance of patents and prototypes. Research Policy, 41(8), 1407-1421.

Bao, Z., & Lu, W. (2020). Developing efficient circularity for construction and demolition waste management in fast emerging economies: Lessons learned from Shenzhen, China. Science of the Total Environment, 724, 138264.

Basmann, R. L., McAleer, M., & Slottje, D. (2007). Patent activity and technical change. Journal of Econometrics, 139(2), 355-375.

Baumann, M., Domnik, T., Haase, M., Wulf, C., Emmerich, P., Rösch, C., ... & Weil, M. (2021). Comparative patent analysis for the identification of global research trends for the case of battery storage, hydrogen and bioenergy. Technological forecasting and social change, 165, 120505.

Berger, N. J., Lindorfer, J., Fazeni, K., & Pfeifer, C. (2022). The techno-economic feasibility and carbon footprint of recycling and electrolysing CO2 emissions into ethanol and syngas in an isobutene biorefinery. Sustainable Production and Consumption, 32, 619-637.

Barth, A. (2018). A deep analysis of chemical structure-based patent searching in the Derwent index space. World Patent Information, 53, 49-57.

Boeing, P., & Mueller, E. (2019). Measuring China's patent quality: Development and validation of ISR indices. China Economic Review, 57, 101331.

Boersma, C., Klok, R. M., Bos, J. M., Naunton, M., Van Den Berg, P. B., de Jong-van den Berg, L. T., & Postma, M. J. (2005). Drug costs developments after patent expiry of Enalapril, Fluoxetine and Ranitidine: a study conducted for the Netherlands. Applied health economics and health policy, 4, 191-196.

Brauneis, R., & Heald, P. (2011). Trademark infringement, trademark dilution, and the decline in sharing of famous brand names: An introduction and empirical study. Buff. L. Rev., 59, 141.

Breitzman, A. F., & Mogee, M. E. (2002). The many applications of patent analysis. Journal of information science, 28(3), 187-205.

Bruhn, S., Sacchi, R., Cimpan, C., & Birkved, M. (2023). Ten questions concerning prospective LCA for decision support for the built environment. Building and Environment, 110535.

Burhan, M., & Jain, S. K. (2012). Tools for Search, Analysis and Management of Patent Portfolios. DESIDOC Journal of Library & Information Technology, 32(3).

Burke, P. F., & Reitzig, M. (2007). Measuring patent assessment quality—Analyzing the degree and kind of (in) consistency in patent offices’ decision making. Research Policy, 36(9), 1404-1430.

Butriy, O. (2016). Interpretation of a numerical range in a patent claim: the understanding of a skilled person. Journal of Intellectual Property Law & Practice, 11(5), 333-338.

Büttner, B., Firat, M., & Raiteri, E. (2022). Patents and knowledge diffusion: The impact of machine translation. Research Policy, 51(10), 104584.

Castillo, M., de Guzman, M. J. K., & Aberilla, J. M. (2023). Environmental sustainability assessment of banana waste utilization into food packaging and liquid fertilizer. Sustainable Production and Consumption.

Caviggioli, F., De Marco, A., Montobbio, F., & Ughetto, E. (2020). The licensing and selling of inventions by US universities. Technological Forecasting and Social Change, 159, 120189.

Chen, L., Xu, S., Zhu, L., Zhang, J., Lei, X., & Yang, G. (2020). A deep learning based method for extracting semantic information from patent documents. Scientometrics, 125, 289-312.

Chen, H., Zhang, G., Zhu, D., & Lu, J. (2017). Topic-based technological forecasting based on patent data: A case study of Australian patents from 2000 to 2014. Technological Forecasting and Social Change, 119, 39-52.

Cho, R. L. T., Liu, J. S., & Ho, M. H. C. (2021). The development of autonomous driving technology: perspectives from patent citation analysis. Transport Reviews, 41(5), 685-711.

Choi, J., Jeong, B., Yoon, J., Coh, B. Y., & Lee, J. M. (2020). A novel approach to evaluating the business potential of intellectual properties: A machine learning-based predictive analysis of patent lifetime. Computers & Industrial Engineering, 145, 106544.

Cockburn, I., Kortum, S., & Stern, S. (2003). Are all patent examiners equal? Examiners, patent characteristics, and litigation outcomes. Patents in the knowledge-based economy, 19, 52-53.

Corpart, J., Grimaldi, S., Gucci, G., M., Maj, P. (2006) Process for synthesizing selected organic peroxides (U.S. Patent No. US8088942). U.S. Patent and Trademark Office.

Crass, D., Garcia Valero, F., Pitton, F., & Rammer, C. (2019). Protecting innovation through patents and trade secrets: Evidence for firms with a single innovation. International Journal of the Economics of Business, 26(1), 117-156.

Cuellar, S., Méndez-Morales, A., & Herrera, M. M. (2022). Location matters: A novel methodology for patent’s national phase process. Journal of the Knowledge Economy, 13(3), 2138-2163.

Daim, T., Lai, K. K., Yalcin, H., Alsoubie, F., & Kumar, V. (2020). Forecasting technological positioning through technology knowledge redundancy: Patent citation analysis of IoT, cybersecurity, and Blockchain. Technological Forecasting and Social Change, 161, 120329.

de la Fuente, B., Tornos, A., Príncep, A., Lorenzo, J. M., Pateiro, M., Berrada, H., ... & Martí-Quijal, F. J. (2020). Scaling-up processes: Patents and commercial applications. In Advances in Food and Nutrition Research (Vol. 92, pp. 187-223). Academic Press.

De Rassenfosse, G., & Jaffe, A. B. (2018). Are patent fees effective at weeding out low‐quality patents?. Journal of Economics & Management Strategy, 27(1), 134-148.

Ding, H., Zhou, D. Q., Liu, G. Q., & Zhou, P. (2020). Cost reduction or electricity penetration: Government R&D-induced PV development and future policy schemes. Renewable and Sustainable Energy Reviews, 124, 109752.

Domeij, B. (2000). Industrial Applicability. In Pharmaceutical Patents in Europe (pp. 19-44). Brill Nijhoff.

El Chami, D., & Daccache, A. (2015). Assessing sustainability of winter wheat production under climate change scenarios in a humid climate—An integrated modelling framework. Agricultural Systems, 140, 19-25.

EPO (2023). Guidelines for Examination in the European Patent Office. Available on-line at: <https://link.epo.org/web/epo_guidelines_for_examination_2023_hyperlinked_en.pdf>

Ernst, H. (1997). The use of patent data for technological forecasting: the diffusion of CNC-technology in the machine tool industry. Small business economics, 9, 361-381.

Fantoni, G., Apreda, R., Dell’Orletta, F., & Monge, M. (2013). Automatic extraction of function–behaviour–state information from patents. Advanced Engineering Informatics, 27(3), 317-334.

García-Cruz, A., Díaz-Jiménez, L., Ilyina, A., & Carlos-Hernández, S. (2022). Prospective life cycle assessment of a based orange wax fungicide. Industrial Crops and Products, 180, 114769.

Haase, M., Wulf, C., Baumann, M., Rösch, C., Weil, M., Zapp, P., & Naegler, T. (2022). Prospective assessment of energy technologies: a comprehensive approach for sustainability assessment. Energy, Sustainability and Society, 12(1), 1-41.

Han, X., Zhu, D., Lei, M., & Daim, T. (2021). R&D trend analysis based on patent mining: An integrated use of patent applications and invalidation data. Technological Forecasting and Social Change, 167, 120691.

Hetherington, A. C., Borrion, A. L., Griffiths, O. G., & McManus, M. C. Use of LCA as a development tool within early research: Challenges and issues across different sectors. International Journal of Life Cycle Assessment, 19(1), 130–143 (2014).

Hu, Y., Jing, X., Ko, Y., & Rayz, J. T. (2020, September). Misspelling correction with pre-trained contextual language model. In 2020 ieee 19th international conference on cognitive informatics & cognitive computing (icci\* cc) (pp. 144-149). IEEE.

Hussin, F., & Aroua, M. K. (2020). Recent trends in the development of adsorption technologies for carbon dioxide capture: A brief literature and patent reviews (2014–2018). Journal of Cleaner Production, 253, 119707.

ISO (2006a). ISO 14040. Environmental management–Life cycle assessment–Principles and framework.

Jaffe, A. B., & Trajtenberg, M. (2002). Patents, citations, and innovations: A window on the knowledge economy. MIT press.

Jalali, S., & Wohlin, C. (2012, September). Systematic literature studies: database searches vs. backward snowballing. In Proceedings of the ACM-IEEE international symposium on Empirical software engineering and measurement (pp. 29-38).

Karkinsky, T., & Riedel, N. (2012). Corporate taxation and the choice of patent location within multinational firms. Journal of international Economics, 88(1), 176-185.

Karp, S. G., Schmitt, C. C., Moreira, R., de Oliveira Penha, R., de Mello, A. F. M., Herrmann, L. W., & Soccol, C. R. (2022). Sugarcane biorefineries: Status and perspectives in bioeconomy. BioEnergy Research, 15(4), 1842-1853.

Kawase, K., Ishii, Y. (2004). Iron base sintered alloy excellent in machinability (Pantent No. EP1605070). European Patent Office.

Kim, S., & Yoon, B. (2021). Patent infringement analysis using a text mining technique based on SAO structure. Computers in Industry, 125, 103379.

Kim, D. H., Lee, B. K., & Sohn, S. Y. (2016). Quantifying technology–industry spillover effects based on patent citation network analysis of unmanned aerial vehicle (UAV). Technological Forecasting and Social Change, 105, 140-157.

Kitamura, Y., Kashiwase, M., Fuse, M., & Mizoguchi, R. (2004). Deployment of an ontological framework of functional design knowledge. Advanced Engineering Informatics, 18(2), 115-127.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. The Quarterly Journal of Economics, 132(2), 665-712.

Krestel, R., Chikkamath, R., Hewel, C., & Risch, J. (2021). A survey on deep learning for patent analysis. World Patent Information, 65, 102035.

Lee, C. (2021). A review of data analytics in technological forecasting. Technological Forecasting and Social Change, 166, 120646.

Liu, W., Song, Y., & Bi, K. (2021). Exploring the patent collaboration network of China's wind energy industry: a study based on patent data from CNIPA. Renewable and Sustainable Energy Reviews, 144, 110989.

Liu, L., Li, Y., Xiong, Y., & Cavallucci, D. (2020). A new function-based patent knowledge retrieval tool for conceptual design of innovative products. Computers in Industry, 115, 103154.

Liu, Q., Wu, H., Ye, Y., Zhao, H., Liu, C., & Du, D. (2018, July). Patent Litigation Prediction: A Convolutional Tensor Factorization Approach. In IJCAI (pp. 5052-5059).

Lupu, M., Mayer, K., Kando, N., & Trippe, A. J. (Eds.). (2017). Current challenges in patent information retrieval (Vol. 37). Heidelberg: Springer.

Ma, B., Pan, S., Shu, X. (2018) Fully continuous flow production process for directly preparing organic peroxide from alcohol or alkane (Patent No. EP3666754). Chinese Patent Office.

Mao, G., Wang, S., Teng, Q., Zuo, J., Tan, X., Wang, H., & Liu, Z. (2017). The sustainable future of hydropower: A critical analysis of cooling units via the Theory of Inventive Problem Solving and Life Cycle Assessment methods. Journal of Cleaner Production, 142, 2446-2453.

Maynard, J. T. (1979). How to read a patent. IEEE Transactions on Professional Communication, (2), 112-118.

Moni, S. M., Mahmud, R., High, K., & Carbajales‐Dale, M. (2020). Life cycle assessment of emerging technologies: A review. Journal of Industrial Ecology, 24(1), 52-63.

Montecchi, T., Russo, D., & Liu, Y. (2013). Searching in Cooperative Patent Classification: Comparison between keyword and concept-based search. Advanced Engineering Informatics, 27(3), 335-345.

Morales-Gonzalez, O. M., Escribà-Gelonch, M., & Hessel, V. (2019). Life cycle assessment of vitamin D 3 synthesis: from batch to photo-high p, T. The International Journal of Life Cycle Assessment, 24, 2111-2127.

Park, J., Lee, H., & Park, Y. (2009). Disembodied knowledge flows among industrial clusters: A patent analysis of the Korean manufacturing sector. Technology in Society, 31(1), 73-84.

Parteka A, & Kordalska A. Artificial intelligence and productivity: global evidence from AI patent and bibliometric data. Technovation, 125, 102764; 2023.

Pénin, J. (2012). Strategic uses of patents in markets for technology: A story of fabless firms, brokers and trolls. Journal of Economic Behavior & Organization, 84(2), 633-641.

Phan, K., & Daim, T. (2013). Forecasting the maturity of alternate wind turbine technologies through patent analysis. In Research and Technology Management in the Electricity Industry: Methods, Tools and Case Studies (pp. 189-211). London: Springer London.

Phillips, M. W. A. (2020). Agrochemical industry development, trends in R&D and the impact of regulation. Pest management science, 76(10), 3348-3356.

Piccinno, F., Hischier, R., Seeger, S., & Som, C. (2016). From laboratory to industrial scale: a scale-up framework for chemical processes in life cycle assessment studies. Journal of Cleaner Production, 135, 1085-1097.

Pizzol, M., & Andersen, M. S. (2022). Green Tech for Green Growth? Insights from Nordic Environmental Innovation. In Business Models for the Circular Economy: A European Perspective (pp. 193-218). Cham: Springer International Publishing.

Pozo, M. D. (2017). The European requirement of industrial application: The Requirement of Industrial Application. In Patenting Genes (pp. 30-61). Edward Elgar Publishing.

Raugei, M., & Winfield, P. (2019). Prospective LCA of the production and EoL recycling of a novel type of Li-ion battery for electric vehicles. Journal of Cleaner Production, 213, 926-932.

Robson, H. (2001). How to read a patent. In Verified Syntheses of Zeolitic Materials (p. 73). Elsevier Science.

Russo, D., Spreafico, M., & Spreafico, C. (2023). Supporting decision making in design creativity through requirements identification and evaluation. International Journal of Design Creativity and Innovation, 1-17.

Russo, D., Spreafico, C., Avogadri, S., & Precorvi, A. (2022). Investigating the Impacts of Misspellings in Patent Search by Combining Natural Language Tools and Rule-Based Approaches. Knowledge, 2(3), 487-507.

Sandén, B. A., & Hillman, K. M. (2011). A framework for analysis of multi-mode interaction among technologies with examples from the history of alternative transport fuels in Sweden. Research policy, 40(3), 403-414.

Sarica, S., Luo, J., & Wood, K. L. (2020). TechNet: Technology semantic network based on patent data. Expert Systems with Applications, 142, 112995.

Shalaby, W., & Zadrozny, W. (2019). Patent retrieval: a literature review. Knowledge and Information Systems, 61, 631-660.

Spreafico, C., Landi, D., & Russo, D. (2023). A new method of patent analysis to support prospective life cycle assessment of eco-design solutions. Sustainable Production and Consumption, 38, 241-251.

Spreafico, C., Russo, D., & Spreafico, M. (2021). Investigating the evolution of pyrolysis technologies through bibliometric analysis of patents and papers. Journal of Analytical and Applied Pyrolysis, 159, 105021.

Sun, Y., Liu, W., Cao, G., Peng, Q., Gu, J., & Fu, J. (2022). Effective design knowledge abstraction from Chinese patents based on a meta-model of the patent design knowledge graph. Computers in Industry, 142, 103749.

Teng, H., Wang, N., Zhao, H., Hu, Y., & Jin, H. (2024). Enhancing semantic text similarity with functional semantic knowledge (FOP) in patents. Journal of Informetrics, 18(1), 101467.

Thonemann, N., Schulte, A., & Maga, D. (2020). How to conduct prospective life cycle assessment for emerging technologies? A systematic review and methodological guidance. Sustainability, 12(3), 1192.

Torrisi, S., Gambardella, A., Giuri, P., Harhoff, D., Hoisl, K., & Mariani, M. (2016). Used, blocking and sleeping patents: Empirical evidence from a large-scale inventor survey. Research policy, 45(7), 1374-1385.

Tsoy, N., Steubing, B., van der Giesen, C., & Guinée, J. (2020). Upscaling methods used in ex ante life cycle assessment of emerging technologies: a review. The International Journal of Life Cycle Assessment, 25, 1680-1692.

Torrisi, S., Gambardella, A., Giuri, P., Harhoff, D., Hoisl, K., & Mariani, M. (2016). Used, blocking and sleeping patents: Empirical evidence from a large-scale inventor survey. Research policy, 45(7), 1374-1385.

van der Giesen, C., Cucurachi, S., Guinée, J., Kramer, G. J., & Tukker, A. (2020). A critical view on the current application of LCA for new technologies and recommendations for improved practice. Journal of Cleaner Production, 259, 120904.

Xu, Y., Zhang, C., He, S., Chen, H. (2021) Preparation method of ultrahigh-sphericity nanometer yttrium oxide dispersion strengthened titanium alloy powder (Patent No. CN114178538). China Patent Office.

Yang, J. (2011). Dual-alloy cladding layer wear plate and preparation method (Patent No. CN102517578). China Patent Office.

Yuan, X., & Li, X. (2021). Mapping the technology diffusion of battery electric vehicle based on patent analysis: A perspective of global innovation systems. Energy, 222, 119897.

Yun, J. J., Won, D., Park, K., Jeong, E., & Zhao, X. (2019). The role of a business model in market growth: The difference between the converted industry and the emerging industry. Technological Forecasting and Social Change, 146, 534-562.

Zhang, H., Daim, T., & Zhang, Y. P. (2021). Integrating patent analysis into technology roadmapping: A latent dirichlet allocation based technology assessment and roadmapping in the field of Blockchain. Technological Forecasting and Social Change, 167, 120729.

1. Life cycle impact assessment (LCIA) has more to do with the natural system, which patent analysis cannot inform much about. Unless there is some wise guidance that LCIA can provide, that might be preferable. [↑](#footnote-ref-1)
2. A patent requires a filing fee and maintenance fees every year otherwise its validity expires. [↑](#footnote-ref-2)
3. A patent can be filed in one state or possibly in one geographical region (as with the European patent). Therefore, its protection can be extended into new countries with new filings, even after some time has passed since the first filing. Different geographical extensions can be maintained or abandoned later. Each extension requires the payment of additional maintenance fees to the respective patent office. [↑](#footnote-ref-3)
4. A patent is typically divided into the following parts: title, abstract, background of invention, description and claims. Only the claims have legal value. The description justifies what is reported in the claims. [↑](#footnote-ref-4)
5. A patent generally reports a range of values rather than a precise value to quantify a parameter. Sometimes a "preferred value" within the range is suggested. This is done to increase the legal protection of the patent in view of variants that can be developed by competitors or future developments [↑](#footnote-ref-5)
6. Along with a patent, other documents are usually found in patent databases. Among them is the search report with the result of the examination and the infringement report that reports oppositions to the novelty and originality that are made by third parties once the patent is granted. [↑](#footnote-ref-6)