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LCI METHODOLOGY AND DATABASES

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

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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 This study suggests which patent analysis techniques can be used to support which prospective LCA challenges, by reviewing patent analysis techniques and classifying the information that can be extracted from them according to those required to meet prospective LCA challenges. To illustrate the usefulness of the suggested techniques, a case study on solid oxide fuel cells is presented.

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 as follows: (i) some information can be intentionally distorted to hinder competitors; (ii) patent bibliometric 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 technology readiness level (TRL) of the prototype from which they were obtained; (v) a less than rigorous data examination process; and (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

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1 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. 2024; Pallas et al. 2020). Compared to standard LCA, the information possible to attain 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 in prospective LCA compared to other types of fields dealing with technological forecasting, e.g. innovation management (Daim et al. 2020), macroeconomy (Parteka and Kordalska 2023) and market research. For example, the studies by García-Cruz et al. (2022), Berger et al. (2022), and 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 the text from a few patents 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. These studies indicate an emerging interest in technological forecasting, which can be further pursued, structured, and refined also to support prospective LCA.

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. Retrieving information on R&D efforts from patents and conducting patent bibliometric analysis for predicting market trends necessitate complementary approaches, tools, time, and resource commitments. The research gap addressed by this study is to suggest which patent analysis techniques can be used to support which prospective LCA challenges. This study first reviews patent analysis techniques by classifying the information that can be extracted from them according to those required to meet prospective LCA challenges. To illustrate the usefulness of the suggested techniques, a case study on solid oxide fuel cells is presented. Patents can thus be used to support prospective LCA, in particular when the practitioner cannot count on the support from technology experts.

2 Materials and methods

In this study, we classified the patent analysis techniques from the literature according to the addressed prospective LCA challenge. The matching between challenges and techniques is based on the information that can be extracted from the patent analysis techniques according to a literature review.

2.1 Considered prospective LCA challenges

In this section, the prospective LCA challenges considered in this study are introduced and related to three of the main steps of the LCA framework: goal and scope definition,

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 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 immature technology at a mature state?
	Select technology alternatives. Which technologies are relevant to study for 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 is unavailable?
Interpretation	**Uncertainty analysis.** How to account for uncertainty due to the future development of the considered technology?

inventory analysis, and interpretation.[1] For each step, the selected challenges, reported through a question, are those which we were able to answer with the selected patent analysis techniques according to what is explained in the considered sources from the scientific literature.

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. 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). Challenges arise also when attempting to select relevant technology alternatives for comparison with currently mature technologies (Arvidsson et al. 2024).

In prospective LCA, the availability of LCI data for technologies at a low technology readiness level (TRL) is limited. This is due to, among others, the focus of LCA databases on mature technologies, 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). 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, but such support is not always available in sufficient measures. 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.

2.2 Patent analysis technique review

Many patent analysis techniques have been proposed in the literature, which implement 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 reliability 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).

Table 2 lists the patent analysis techniques identified in the literature review.

We tested the parts of the proposed approach on a case study (see Section 3.4) to demonstrate their potential.

[1] Life cycle impact assessment (LCIA) has more to do with the natural system, which patent analysis cannot inform much about.

Table 2 Considered patent analysis techniques

Overarching patent analysis techniques	Specific patent analysis techniques	Sources
Patent bibliographic analysis retrieves information about patent owners, maintenance costs, and geographical coverage	**Patent cost analysis** monitors who invest and how much to maintain a patent "alive", which is correlated with the interest in its future development. This is because the patent requires a filing fee and maintenance fees every year; otherwise, it expires	Russo et al. (2023), Kogan et al. (2017), Choi et al. (2020), Spreafico et al. (2021)
	Patent geographical coverage[a] analysis determines in which country the patent has been filed and is maintained "alive", indicating potential future markets	Yuan and Li (2021), Yuan and Li (2021), Cuellar et al. (2022), Karkinsky and Riedel (2012), Caviggioli et al. (2020), Torrisi et al. (2016)
Patent bibliometrics uses the same indicators as bibliometrics of scientific documents to analyse patent trends	**Temporal distribution of patent publication** evaluates the diffusion over time of the patent activity	Phan and Daim (2013), Adamuthe and Thampi (2019), Mao et al. (2017)
	Citations analysis evaluates the popularity of a patent according to the citations received, typically by other patents	Kim et al. (2016), Chen et al. (2020)
Patent mining is used to collect qualitative and quantitative information from patent texts	**Function extraction** from the patent describes the functioning of the technology	Liu et al. (2020), Fantoni et al. (2013), Kitamura et al. (2004), Sun et al. (2022)
	Information retrieval about industrial applicability reveals how the patent owner intends to manufacture the claimed technology	Chen et al. (2017), Sun et al. (2022)
	Collection of different information from different parts[b] of the patent discriminates 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 retrieves numerical values for certain parameters of the described technologies	Butriy (2016), Spreafico et al. (2023), Hussin and Aroua (2020)
	Patent data range[c] analysis discriminates the part of a range of parameter values deriving from experiments or measurements used to increase the legal protection of the patent	Butriy (2016)
Additional documents[d] analysis is used to evaluate patent quality	**Infringement analysis** evaluates whether and when a patent has been accused of plagiarising other patents	Pénin (2012) (Liu et al. 2018). Breitzman and Mogee 2002; Brauneis and Heald 2011

[a] 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

[b] 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

[c] 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

[d] 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

3 Results

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

3.1 Goal and scope definition in prospective LCA

3.1.1 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.

3.1.2 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 field of prospective LCA (Phan and Daim 2013; Adamuthe and Thampi 2019; Mao

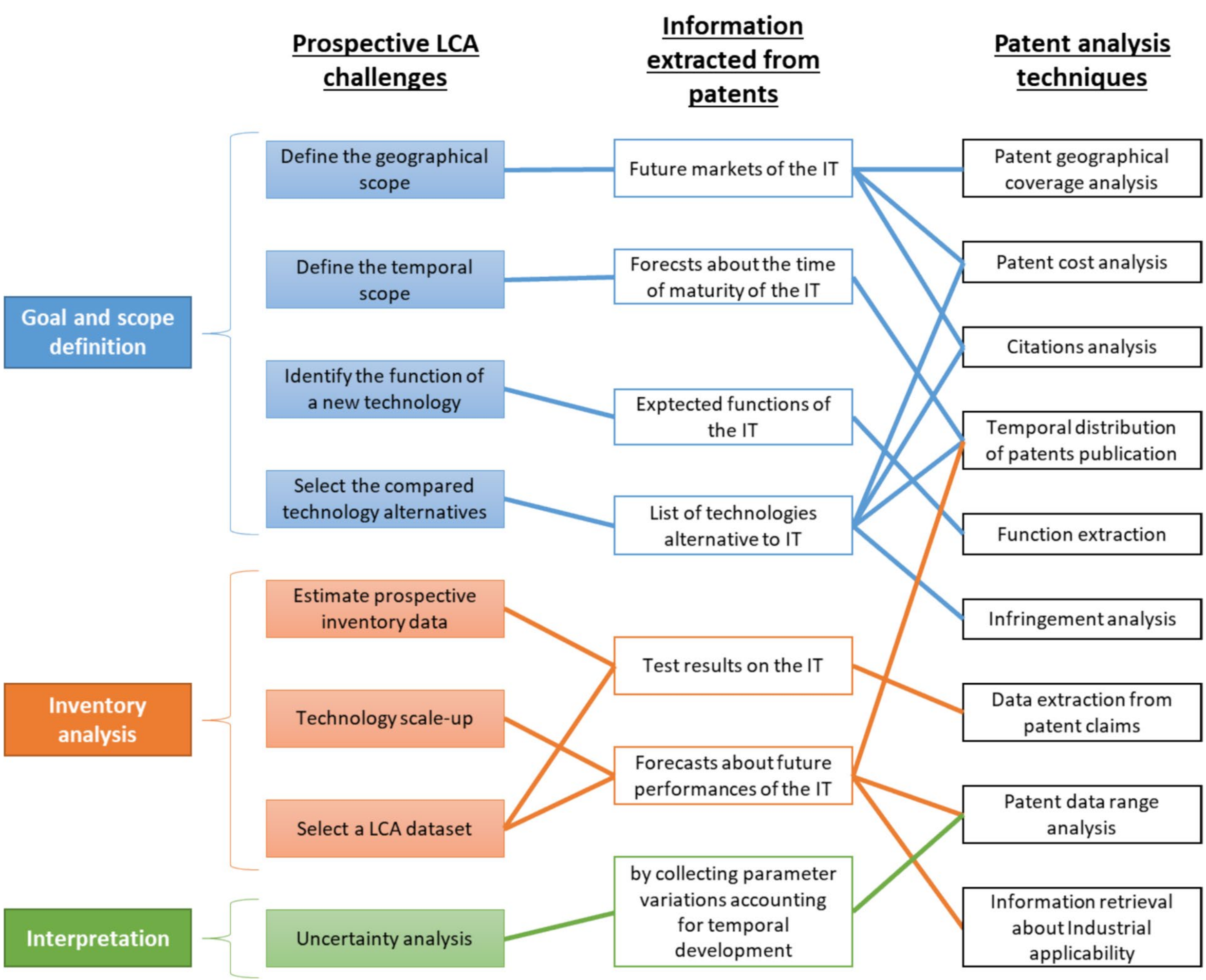

Fig. 1 Identified matches between prospective LCA challenges, information extracted from patents, and patent analysis techniques (where IT = immature technology)

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 Fig. 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, based on this hypothesis, it is possible to reconstruct the missing traits of the curves of a new technology (see Fig. 2 right) through the comparison with the curves of a similar technology class (Fig. 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 Fig. 2 right).

While the patent publication-based approach may not precisely predict the future shape of technological evolution, it offers a structured way to monitor and interpret trends. The strength of this method lies in its ability to highlight shifts in innovation activity, helping to inform strategic decisions in an otherwise uncertain landscape (Phan and Daim 2013; Adamuthe and Thampi 2019).

3.1.3 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 a 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.

In order to automate the extraction of the function, overcoming the ambiguity with which it is referred to in the patents and patent analysis techniques (e.g. the objective in Liu et al. (2020) and the working principle in Fantoni et al. (2013), a taxonomy can be integrated with patent analysis (Spreafico and Russo 2023).

3.1.4 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 following:

- 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; Russo et al. 2023). 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

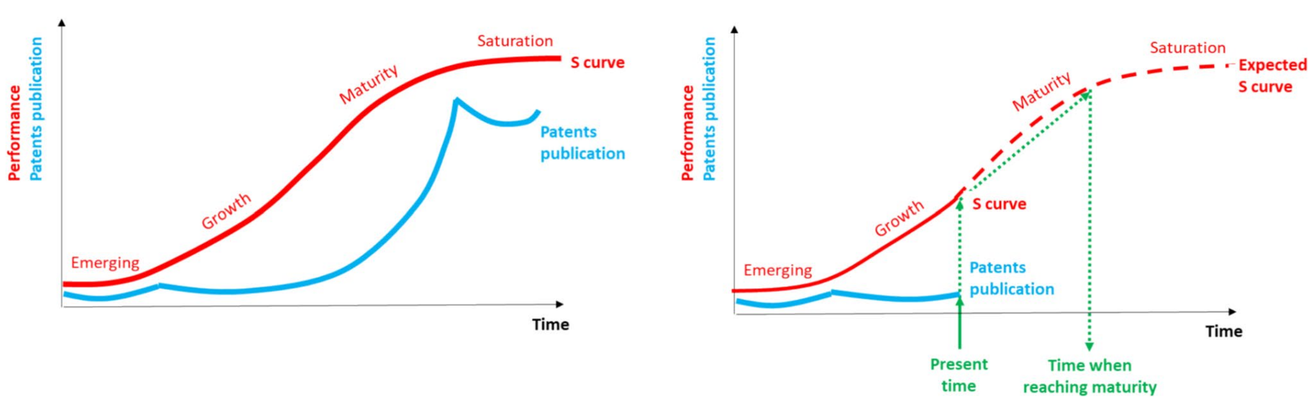

Fig. 2 (left) Comparison between publication trend and S curve (adapted from Ernst 1997) and (right) its use to predict when the immature technology will reach maturity (time of the study)

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).

Since patents of famous owners are more widespread and well-known, they typically receive more infringement without necessarily having more chances of being developed (Breitzman and Mogee 2002; Brauneis and Heald 2011). Therefore, to overcome this problem, the infringement analysis can be associated with commercial analyses on the notoriety of the patent owners.

3.2 Inventory analysis

3.2.1 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 is 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.

3.2.2 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 (Fig. 3).

Since the upscaling and maturity forecasting approaches are effectively equivalent, the limitations as described in Section 3.1.2 apply.

Experts' opinions about data upscaling can be collected from patents by using the following patent analysis techniques.

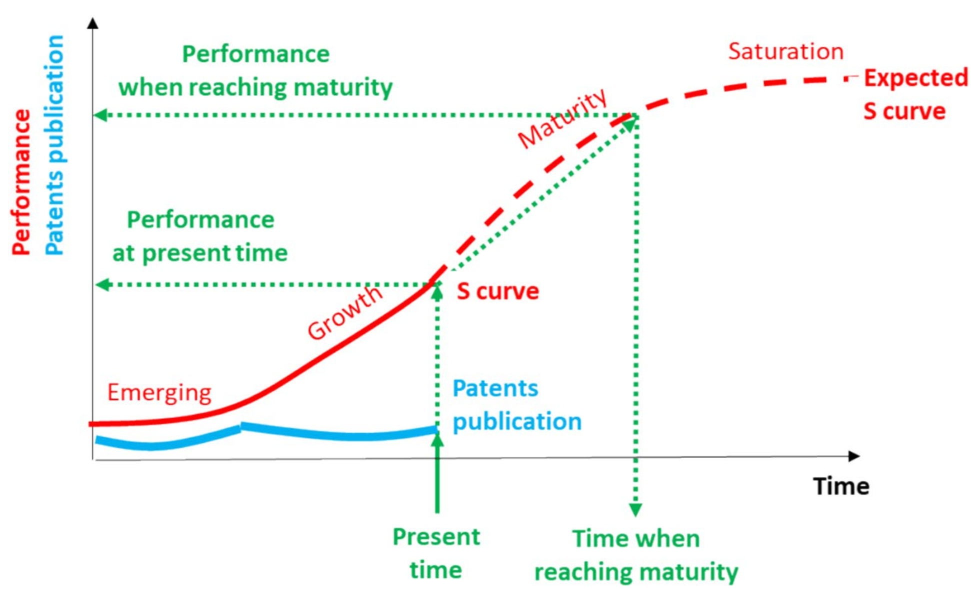

Fig. 3 Comparison of the temporal distribution of the patent publication and the S curve to support scale-up by predicting the performance of a parameter at technological maturity (adapted from Mao et al. 2017)

- 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 30,000 and 35,000 rpm. In the description, on the contrary, it only reports experimental tests referring to a rotation of 35,000 rpm. One can therefore assume the intention of the patent owner to achieve a lower rotation speed at technological maturity (i.e. 30,000 rpm).
- The industrial relevance of the patented technology can be analysed by collecting information about up-scaling (Sun 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".

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 can be assumed to represent a prospective result of the technology at maturity. This can be seen in, for example, the patent CN114178538.

Integration with other knowledge sources to collect manufacturing data is essential if patent attorneys 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).

3.2.3 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-W 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 the 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.

3.3 Interpretation

3.3.1 Uncertainty analysis

To evaluate the uncertainty about the future development of the considered technology, patent data range analysis can be applied, albeit with the same limitations as in the application of upscaling (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.

3.4 Case study

In order to exemplify how patents can be used to support prospective LCA, a case study about solid oxide fuel cells (SOFCs) is presented. A SOFC is an electrochemical device converting methane or syngas or biogas or hydrogen into electrical energy (direct operation) through an electrochemical reaction. The SOFC can also be operated in reverse to produce hydrogen from water by consuming electricity (reverse operation). An anode, a cathode, and a ceramic electrolyte in between make up the SOFC core structure. These three components are arranged in a tubular or planar shape. During use, the hydrogen is delivered to the external side of the anode, while an oxidant (typically air) is delivered to the external side of the cathode. The electrolyte conducts oxygen ions from the cathode to the anode, where it reacts with the hydrogen. The electrochemical reaction generates electricity with high efficiency. In the considered SOFC, the anode consists of nickel oxide and yttrium-stabilised zirconia (YSZ). The electrolyte consists of YSZ. The cathode consists of strontium-doped lanthanum manganite (LSM) and YSZ. Figure 4 schematically represents the typical structure of the SOFC with a planar and tubular layout with the main components.

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 patent publication	Predict the maturity level of the immature technology according to the patent 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 patent 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 is 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

3.4.1 Identifying the function

It is important to correlate a document used in the LCA, relating to a technology, to the function performed, to guarantee the consistency of the analysis with the functional unit. To understand whether it is more common to declare the function performed in a patent or a scientific paper, a query search was carried out in Orbit DB for patents and in Scopus for articles. Here, we could isolate two document pools. The following query is used to retrieve the patents: “(((SOLID OR OXIDE +) 2D FUEL + 1D CELL +) OR SOFC)/TI/AB/DESC/CLMS”. This query was launched in all fields of the patent, filtering those granted, to have greater guarantees on the reliability of the content. In total, the set contains 19,495 patents. We further obtained the pool of scientific papers with the query: “ALL(((SOLID OR OXIDE*) W/2 FUEL* W/1 CELL*) OR SOFC)”. This query is equivalent in structure to that used for patents and has been launched in all fields of scientific papers. In this case, we preserved only the “peer-reviewed articles”, i.e. the papers published in international scientific journals. In total, the set contains 92,144 articles.

Then, within each pool, we searched for how many documents claim to perform some functions of the arbitrarily chosen SOFCs: process methane, process syngas, process biogas (referred to the direct operation), and produce hydrogen (referred to the reverse operation). This was done by launching queries related to each function within the respective pool: the initial query, relating to the SOFC search, was combined with “AND” logical operator with a query relating to the function search.

Table 4 reports the percentages of patents and articles, within their respective pool, referring to the listed functions and the queries used to retrieve them. As can be seen, for most functions searched (except process biogas), a greater number of patents than articles have been retrieved. This indicates a greater propensity to declare the functions performed in patents rather than in articles, which helps the LCA practitioner to define the functional unit of the emerging technology using patents.

3.4.2 Selecting the technology alternatives

To select a technological alternative to SOFCs, we analysed the temporal distribution of patent publications, comparing the SOFC patents (obtained with the query presented in Section 5.1) with those of the proton exchange membrane fuel cell (PEMFC). This is because PEMFCs are today considered the main alternative to SOFCs (Yan et al. 2020). At the same time, the publication trends of scientific articles about SOFC and PEMFC were also compared. The analysed documents were obtained through queries launched in the title and abstract, to narrow the field to documents dedicated to SOFC and PEMFC. The query to get the SOFC articles is “((SOLID OR OXIDE*) W/2 FUEL* W/1 CELL*) OR SOFC”, the query to obtain PEMFC patents is “(PROTON + 2D FUEL + 1D CELL +) OR PEMFC”, and the query to get PEFC articles is “(PROTON* W/2 (FUEL* W/1 CELL*)) OR PEMFC”.

Figure 5 compares the temporal trends of publication of articles and patents by SOFC and PEMFC from 2004 to 2024. As can be seen, the number of articles is growing, albeit at different rates in recent years. For patents, however, a steep growth in PEMFC can be seen currently, after an initial stagnation, which is balanced by a decrease in SOFC patents in recent years. It follows that only by comparing the trends of the patent publication, a technological transition from SOFCs to PEMFCs can be suspected, making it reasonable to consider the latter as technology alternative in prospective LCA. This type of information can be used to derive average or marginal technology mixes for use in attributional and consequential models, respectively.

In addition, the use of the S-curve is a further proof of the potential of PEMFC to be recognised as an alternative to SOFC. This can be done by qualitatively overlaying the S-curves on the patent publication trend graphs of SOFC and

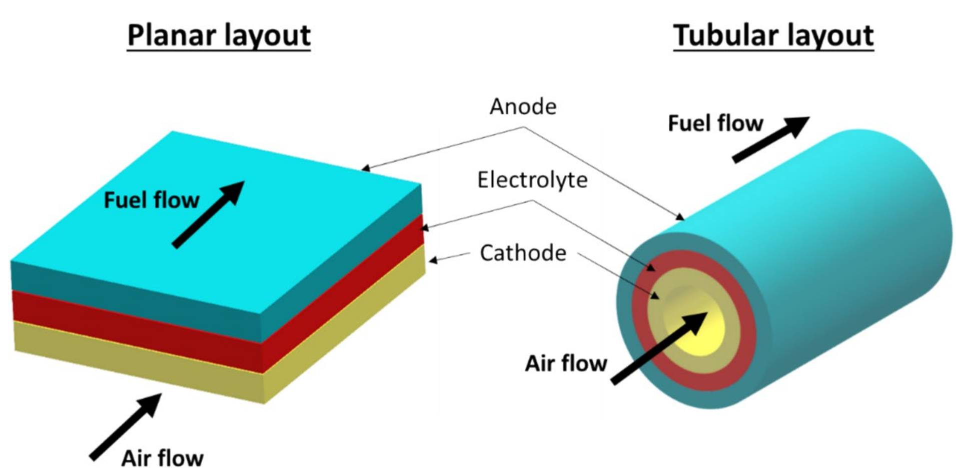

Fig. 4 Structures of the considered SOFCs (Spreafico 2024)

Table 4 SOFCs patent and article classification according to different functions

Function	Patents	Articles	Query (referred to as Orbit syntax)	Query (referred to as Scopus syntax)
Process methane	13%	11%	((PROCESS + OR TRANSFORM + OR FUEL +) 1D (METHAN + OR CH4))/TI/AB/DESC/CLMS	ALL((PROCESS* OR TRANSFORM* OR FUEL*) W/1 (METHAN* OR CH4))
Process syngas	4.17%	1.77%	(((PROCESS + OR TRANSFORM + OR DISPOS + OR FUEL +) 1D (SYNGAS + OR (SYNTH + 1D GAS +) OR PYGAS + OR (PYROL + 1D GAS +)))/TI/AB/DESC/CLMS OR (C01B-2203 +)/CPC/IPC)	ALL((PROCESS* OR TRANSFORM* OR DISPOS* OR FUEL*) W/1 (SYNGAS* OR (SYNTH* W/1 GAS*) OR PYGAS* OR (PYROL* W/ GAS*))
Process biogas	0.70%	1.90%	(((PROCESS + OR TRANSFORM + OR DISPOS + OR FUEL +) 1D (BIOGAS + OR BIOMETHAN + OR (RENEWABLE 1D NATURAL 1D GAS +) OR RNG))/TI/AB/DESC/CLMS OR (B01D-2258 +)/CPC/IPC)	ALL((PROCESS* OR TRANSFORM* OR DISPOS* OR FUEL*) W/1 (BIOGAS* OR BIOMETHAN* OR (RENEWABLE W/1 NATURAL W/1 GAS*) OR RNG))
Produce hydrogen (in SOFC reverse operation)	33%	21%	(HYDROLYSIS OR ((PRODUC + OR GENERAT + OR OBTAIN +) 1D (HYDROGEN OR H2)))/TI/AB/DESC/CLMS	ALL(HYDROLYSIS OR ((PRODUC* OR GENERAT* OR OBTAIN*) W/1 (HYDROGEN OR H2)))
Total	**51%**	**35%**		

PEMF, see Fig. 6. In this way, it is clearly visible that today, the SOFC is in the saturation section of the S-curve, while the PEMFC is in the growth section.

If the PEMFC is not known as a SOFC alternative technology to produce hydrogen, it can be retrieved from patent analysis. To do this, the query "((FUEL 1D CELL +) S (HYDROLYSIS OR ((PRODUC + OR GENERAT + OR OBTAIN +) 1D (HYDROGEN OR H2))))/TI/AB/DESC/CLMS" has been launched in Orbit. The patents obtained were classified according to their patent classes (CPC, Cooperative Patent Classification), using an automatic Orbit function (see Fig. 7 top). Then, using the CPC index in Espacenet (see Fig. 7 bottom), the classes with the highest frequency of patents were searched for. As you can see, the "H01M 8/10" (reported as "H01M-008/10" in Orbit) refers to PEMFCs, i.e., fuel cells having "Polymeric electrolyte membranes".

3.4.3 Estimate prospective inventory data and technology scale-up

In order to discuss the usefulness of patents in prospective LCI, data about SOFCs extracted from patents have been compared with those extracted from articles. The comparison was carried out on data relating to the following parameters: electrolyte thickness, anode functional thickness, anode support thickness, cathode thickness, specific power of the cell during the driving condition, or by excluding the peak power. These parameters were chosen as they are directly related to the quantity of material present in the SOFC and its performance. The data was extracted only from the patents obtained from the query "(((SOLID OR OXIDE +) 2D FUEL + 1D CELL +) OR SOFC)/TI/AB/DESC/CLMS", limiting the selection from 2014 to today, through Orbit Intelligence which reports them (see Table 5). No patents filed after 2022 were collected due to the embargo period to which patents are subjected before evaluation.

Table 6 reports the data relating to the same parameters extracted from the articles.

In order to compare the data extracted from patents and articles, their arithmetic mean, standard deviation, max and min value, and standard error of the mean have been reported in Table 7. As can be seen, the total thickness of the cell (obtained from the sum of electrolyte thickness, anode functional thickness, anode support thickness, and cathode thickness) is lower than that extracted from articles, while the specific power is higher in patents than in articles. This result places patents as better candidates than articles to provide a prospective image of the evolution of SOFCs, since their technological development points towards reducing thickness and increasing specific power (Pirou et al. 2022). In addition, the comparison of the max and min values shows that the patents provide a broader picture of the values associated with the parameters, while anode functional

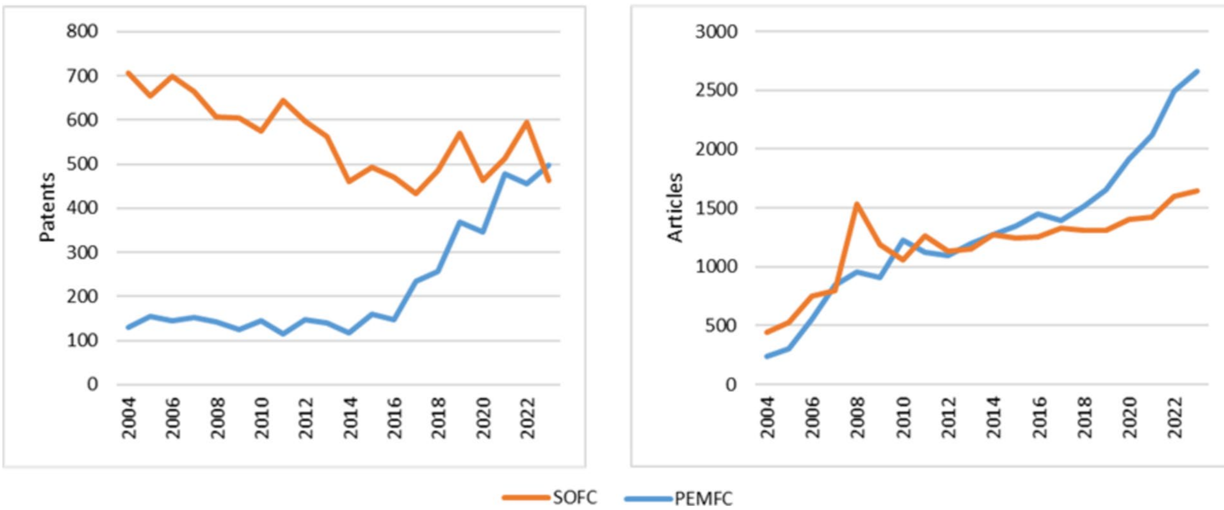

Fig. 5 Comparison of patent (left) and article (right) publication trend of SOFCs and PEMFCs

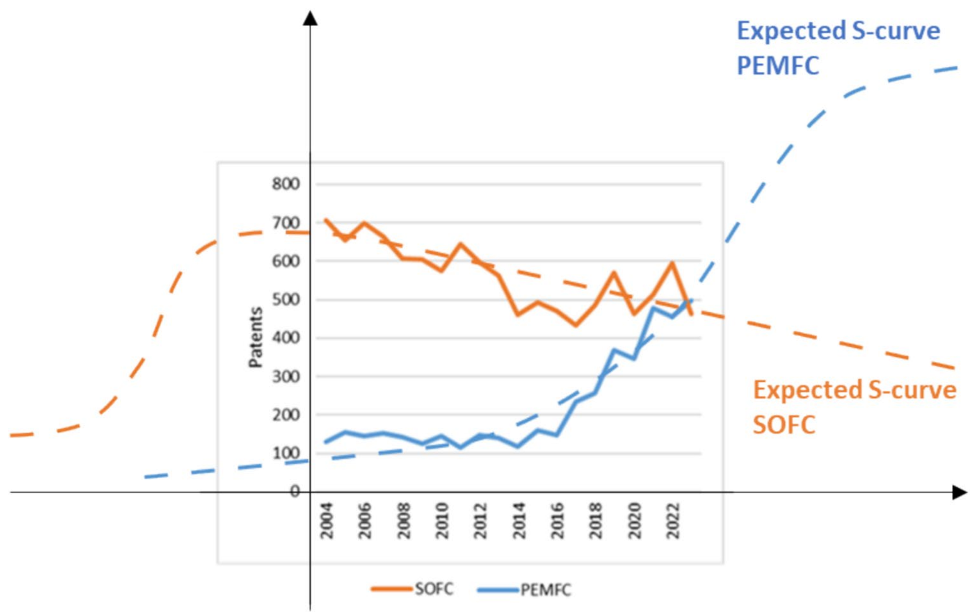

Fig. 6 Qualitative comparison patent publication trend of SOFCs and PEMFCs and S-curves

thickness, anode support thickness, and specific power have a lower standard error of the mean, which is a measure of the uncertainty of your mean lower in patents than in articles. This shows that patents, having more data, allows getting more robust estimates and lower uncertainty on these estimates.

Figure 8 reports the temporal distribution of the data extracted from the considered patents. The resulting trends are aligned with the technological evolution of the SOFCs. Therefore, these trends could boost the LCA practitioner in assuming; for the inventory of these parameters, estimates are more optimistic than the average values reported in Table 7, in view of technology upscaling. Furthermore, since patents can provide a larger number of measurements (samples), empirical estimates of uncertainty for parameters, including information on the type of distributions and mean and standard deviation values, are more robust.

3.4.4 Select an LCA dataset

To extract information to select LCA datasets, the analysis of the collected patents reveals some supporting information. For instance, patent CN113328113 provides specific detail about the machine, i.e. a selective laser melting, used to realise the protective coating of the claimed SOFC: "… the additive manufacturing approach is a selective laser melting technique, the manufacturing process conditions include: the laser power is 100-300W, the scanning speed is

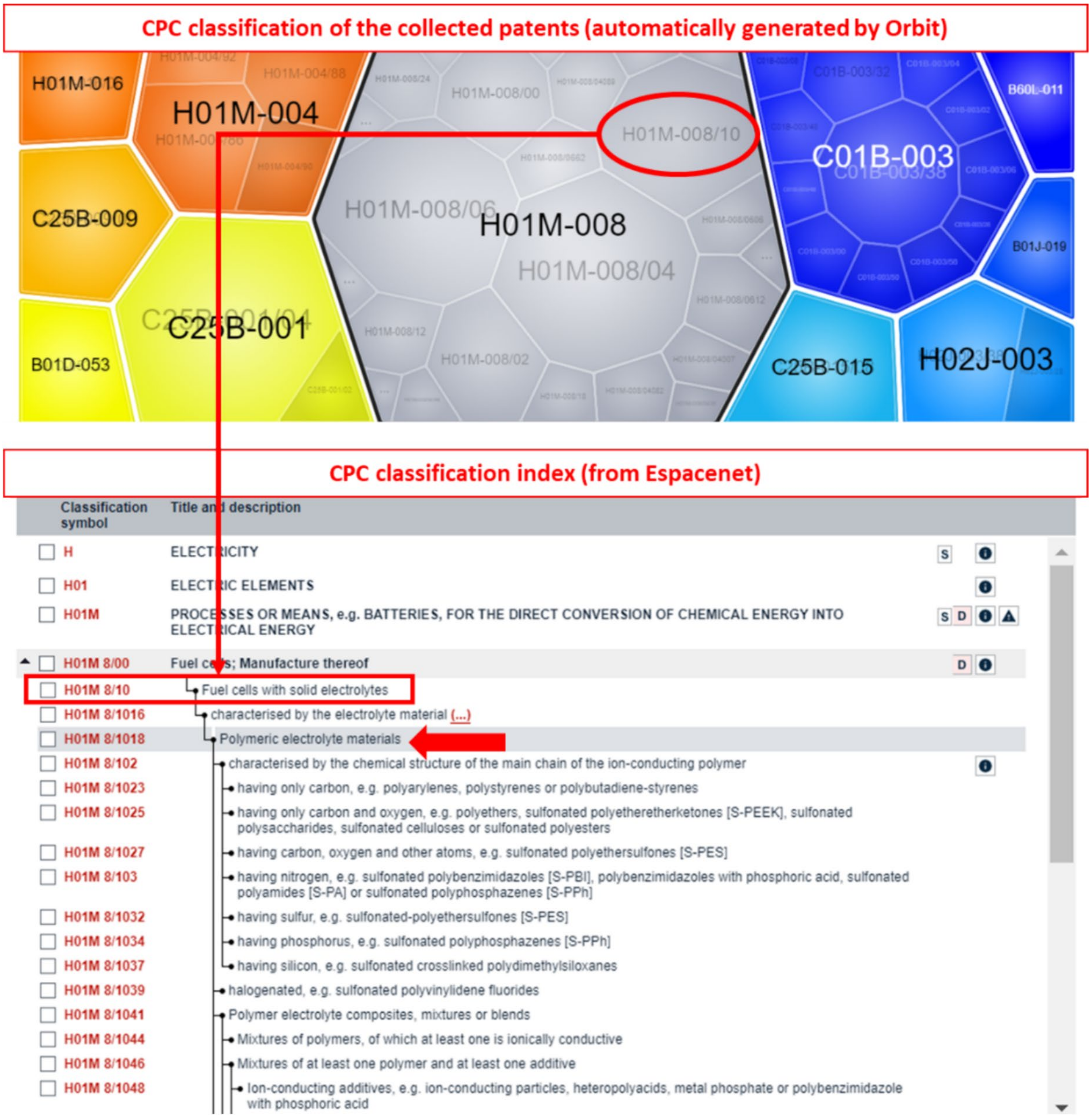

Fig. 7 Automatic classification of patents about fuel cells for hydrogen production into CPC classes provided by Orbit (top) and CPC index from Espacenet (bottom), used to automatically identify PEMFC (i.e. fuel cell with polymeric electrolyte membrane) as candidate technology

300-1200 mm/s, the spot size is 30–100 µm, and the laser wavelength is 500–1070 nm". These information are useful to select the dataset "Laser machining, metal, with YAG-laser, 120W power—RER Europe" from the Ecoinvent database version 3.9. This is because the laser modelled in this dataset operates within the ranges of wavelength, power, and scanning speed declared in the patent, as can be learned from the description provided by Ecoinvent.

Then, the data extracted from the patents about the SOFC can be used in prospective LCA to calculate the environmental impacts. The related life cycle impacts assessment, the obtained results and their discussion are all reported in Spreafico (2024).

4 Discussion

4.1 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

Table 5 Data extracted from SOFC patents

Patent	Year	Electrolyte thickness [mm]	Anode functional thickness [mm]	Anode support thickness [mm]	Cathode thickness [mm]	Specific power [W/cm^2]
CN104022303 max	2014	0.028		0.800		0.320
CN104022303 min	2014	0.021		0.500		0.300
CN104466199	2014			0.100		
CN103887550 min	2014			0.600	0.010	
CN103887550 max	2014			0.900	0.030	
WO2017/092086 min	2015	0.002				
WO2017/092086 max	2015	0.010				
CN106450352	2016					0.335
CN106207221 min	2016	0.010			0.020	
CN106207221 max	2016	0.035			0.040	
US20180115008 min	2016		0.015			
US20180115008 max	2016		0.025			
JP2017123231 min	2016	0.002	0.010	0.150	0.007	
JP2017123231 max	2016	0.020	0.030	0.500	0.060	
EP3516718	2016	0.005	0.020		0.315	
JP2019079747 min	2017	0.005	0.010	0.500		
JP2019079747 max	2017	0.010	0.010	0.500		
EP3430666 min	2017		0.020		0.315	0.440
EP3430666 max	2017		0.020		0.315	0.540
WO2019/205855 max	2018	0.020	0.010		0.005	
WO2019/205855 min	2018	0.001	0.010		0.020	
CN109378488 max	2018	0.050				
CN109378488 min	2018	0.001				
KR10-2019–0024749 min	2018	0.035				0.300
KR10-2019–0024749 max	2018	0.040				0.300
US20190097243	2018					0.300
US20190123362 max	2018	0.010	0.055	0.5		0.380
US20190123362 min	2018	0.010	0.055	0.100		0.380
JP2020071987 max	2018	0.010		0.500	0.010	
JP2020071987 min	2018	0.003		0.500	0.003	
CN109818021 max	2018					0.530
CN109818021 min	2018					0.259
CN109888303	2019		0.010		0.010	0.300
WO2019/167811	2019					0.500
JP2019212642 max	2019	0.005		0.3		
JP2019212642 min	2019	0.001		0.3		
WO2020/191829 min	2019	0.002	0.005	0.400	0.020	0.360
WO2020/191829 max	2019	0.010	0.010	0.500	0.025	0.520
WO2020/208861	2019	0.001	0.005	0.200		
WO2021/005810	2019	0.001		0.200	0.020	
CN112072137 max	2020	0.005		0.400	0.050	0.371
CN112072137 max	2020	0.010		0.400	0.050	0.528
KR10-2021–0135154	2020	0.010				
TWI783307 max	2020	0.001	0.002		0.004	
TWI783307 min	2020	0.003	0.003		0.001	
KR10-2022–0006372	2020	0.001	0.001		0.001	
IN202121045468 max	2021	0.020				0.610
IN202121045468 min	2021	0.005				0.360

Table 5 (continued)

Patent	Year	Electrolyte thickness [mm]	Anode functional thickness [mm]	Anode support thickness [mm]	Cathode thickness [mm]	Specific power [W/cm^2]
CN113285084 max	2021	0.001			0.003	0.500
CN113285084 min	2021	0.001			0.003	0.350
CN113800571	2021	0.001		0.4	0.001	0.338
CN114335640 min	2021	0.005	0.005	0.3	0.001	0.350
CN114335640 max	2021	0.050	0.050	1.5	0.001	0.430
CN115084614 max	2022	0.006	0.004		0.001	
CN115084614 min	2022	0.005	0.003		0.001	

Table 6 Data extracted from SOFC articles

Article	Year	Electrolyte thickness [mm]	Anode functional thickness [mm]	Anode support thickness [mm]	Cathode thickness [mm]	Specific power [W/cm^2]
Lee et al. (2015)	2015	0.010		0.500	0.050	0.400
Mehmeti et al. (2016)	2016					0.300
Rillo et al. (2017)	2017	0.010	0.020	0.450	0.030	0.400
Gandiglio et al. (2019)	2019	0.010	0.010	0.700	0.050	0.156
Smith et al. (2019)	2019	0.014	0.001	0.800	0.049	
Bicer and Khalid (2020)	2020					0.400
Naeini et al. (2022)	2022					0.400
Lai and Adams (2023)	2023					0.437

Table 7 Comparison of data extracted from patents and articles

Comparison criteria	Sources	Electrolyte thickness [mm]	Anode functional thickness [mm]	Anode support thickness [mm]	Cathode thickness [mm]	Specific power [W/cm^2]
Arithmetic mean	Patents	0.011	0.016	0.431	0.046	0.396
	Articles	0.011	0.010	0.613	0.045	0.356
Standard deviation	Patents	0.013	0.016	0.220	0.094	0.097
	Articles	0.002	0.010	0.165	0.010	0.098
Max value	Patents	0.050	0.055	0.900	0.315	0.610
	Articles	0.014	0.020	0.800	0.050	0.437
Min value	Patents	0.001	0.001	0.100	0.001	0.259
	Articles	0.010	0.001	0.450	0.030	0.156
Max–min value	Patents	0.049	0.054	0.800	0.314	0.351
	Articles	0.004	0.019	0.350	0.020	0.281
Standard error of the mean	Patents	0.002	0.003	0.052	0.018	0.019
	Articles	0.001	0.005	0.083	0.005	0.037

patent examiner. The text may therefore be full of synonyms, generic or little-used terms, and even sometimes 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

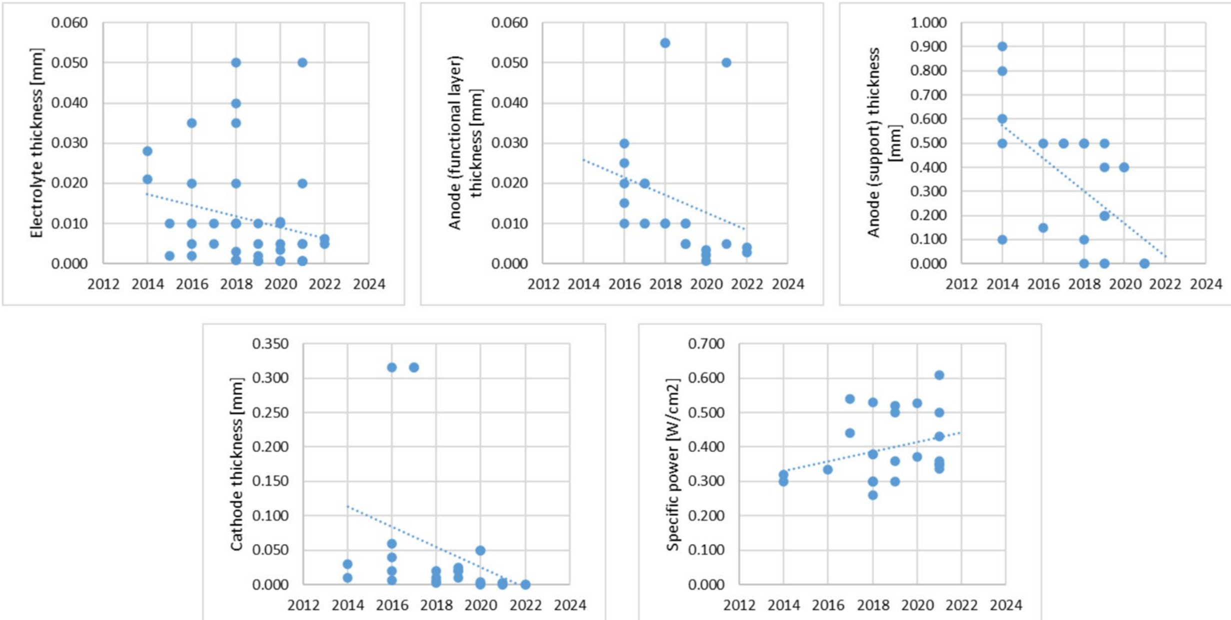

Fig. 8 Temporal trends of the parameters considered in the SOFCs patents

(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 applied, 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).

4.2 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 a 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

Table 8 Comparison between three selected patent databases

Patent database features	Espacenet (owned by the European Patent Office)	Google patents	PatentScope (owned by the World Patent Organization)
Web link	Worldwide.espacenet.com, Register.epo.org	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)

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).

4.3 Where to retrieve data from patents

Many of the most popular patent databases have long allowed patents to be collected and semi-automatically extracted, thereby making available much of the information that has been described in this study. However, not all databases are openly available or allow the processing of information as required.

To support the prospective LCA practitioner in collecting and analysing patents, a selection and comparison of patent databases is reported in Table 8. Those presented are the most diffused patent databases with open access and indexing of all patents worldwide. The comparison considers the ability of each patent database to access the information presented in this study.

5 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 aids to manage 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 opportunities for using patents to support prospective LCA are (i) the identification of future markets, (ii) the prediction of the time when the technology will research maturity, (iii) the identification of the functions of technologies not yet on the market, (iv) the monitoring of the interest of industries in patenting or patented new technologies, (v) the collection of experimental data and data scale-up, and (vi) the identification of relevant immature manufacturing processes and technologies.

Thanks to the results of this study, we believe that practitioners can now autonomously analyse and use patents in a relevant way in prospective LCA. We also believe that a patent analysis expert can extract more information from patents.

The case study of SOFCs showed that the data extracted from patents can differ from those extracted from scientific articles, showing a different perspective with generally more relevant insights for prospective LCA.

Data availability The authors confirm that the data supporting the findings of this study are available within the article and/or its supplementary materials.

Declarations

Conflict of interest The authors declare no competing interests.

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