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On the intersection between prospective LCA and patent analysis. A theoretical discussion

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Abstract

The prospective life cycle assessment (pLCA) methodology allows to estimate the future environmental impacts of emerging technologies and immature products not yet on the market. To make up for the lack of information on the product, the pLCA makes extensive use of secondary data, taken from various sources including patents which contain prospective information of industrial interest. To date, there have been attempts to show the potential of patent analysis in supporting pLCA, but never extensively and as proposed in this work with a truly systematic approach. In fact, this study aims to demonstrate how an accurate analysis of the information contained within patents can provide solutions to a number of open problems underlying the pLCA. More specifically, it was shown how patents can serve for: the support to experts in technological forecasting, the definition of scenario ranges, the support to the background and foreground systems modelling, the comparison of the future diffusion of a mature and an emerging technology, the support to the projections based on pathways to reach policy reductions to ensure time consistency. For each question, it was explained how to decline the patent analysis, i.e. which parts of the patents to analyse and how.

Keywords: prospective LCA; patent analysis; emerging technologies; eco-design; ex-ante LCA

1. Introduction

Prospective Life Cycle Assessment (pLCA) is a long-established practice for estimating the environmental impacts of an emerging technology, an immature product, or a project idea.

The utility of the pLCA is high because this new perspective vision changes the role of the classic LCA. From a tool for estimating the sustainability of a finished product or process, pLCA becomes a tool to support the different product design phase, to be used from the early stages of a product's development [1]. To do this, in the pLCA the future evolution of the product's life cycle input-output must be hypothesized, and this prospective activity must be done in a reliable way to ensure the analysis reliability according to the reference standards, i.e., ISO 14040 [2] and ISO 14044 [3]. The task is very complicated because numerous aspects of the product development must be considered. The immature product and its components may undergo technological evolution, as well as the technologies involved in maintenance, production processes and end-of-life phases.

The reference scenario may change at an energy, climatic, political and economic level, as well as the methods of use of the product by the user. The mutability of all these aspects affects the pLCA in different ways. The function unit, the compared systems and the system boundaries may change to consider the evolution of the product [4].

In the inventory phases, it is necessary to consider different scenarios to hypothesize the evolution of the data both for those on which the product designer has no influence, e.g., electricity mix, that those on which it influences, e.g., prospective characteristics of the product [5]. In particular, prospective scenarios can be drawn from the literature in the first case and from simulations and tests on the immature product in the

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second. However, in the latter case, it is also necessary to consider the role of scalability since the data collected on the immature product in the laboratory or in pilot operation can vary considerably compared to that of the final product in the operational context [6].

Many authors in the literature have proposed many approaches, methods and tools to support pLCA in meeting reliability requirements. Nonetheless, several open problems remain in the scientific literature. One of the most promising approaches is the possibility of integrating patent analysis to support the definition of prospective scenarios [8][9].

However, those who responded to this appeal did so only partially and never consider all the required aspects. Most authors only considered a very small number of patents, often without using a specific analysis strategy [10][11].

Some authors have increased the number of patents considered but analyzed them only at a bibliometric level [12][13].

Only [14] proposed a systematic and semi-automatic method to extract technical information from large number of patents, in compliance with LCA data quality requirements. However, the contribution of this article is limited to the definition only of the technological forecasting scenario of the product and not of the other elements of its life cycle or the pLCA phases (e.g., definition of the functional unit or system boundaries).

In the literature there are scientific journals (e.g., Technology Forecasting and Social Change, Technovation) collecting many articles about approaches, methods, and tools for extracting information from patents to support technological forecasting (e.g., [15], [16], [17]). Then, there is also a substantial line of research, whose articles are published mainly in the magazine World Patent Information, dedicated to the analysis of the quality of the data present in a patent. However, in these lines of research, no one has proposed using patent analysis to support pLCA.

To fill this gap, this study takes a wide-ranging look at the advantages and difficulties to be overcome at the intersection of pLCA and patent analysis. In this regard, the open problems emerging from pLCA literature and the solutions provided at a general level by the literature about patent analysis methods and tools were compared. The study is organized as follows. Section 2 presents the methodology followed to select and analyse the sources. Section 3 presents the obtained results by comparing open problems about pLCA and solutions from patents analysis potentialities. Section 4 discusses the results and draws the conclusions.

2. Methodology

The study has been conducted following a systematic approach. First, pLCA open problems and approaches, methods and tools for performing patent analysis have been collected from the scientific literature by using the following keywords: prospective Life Cycle Assessment, patent analysis, patent search, patent intelligence. The keywords were selected iteratively through the literature review by using the most widespread terms in the pertinent documents. The sources were selected by manually analyzing title and abstract, and the pertinent ones were manually analyzed in full text.

Then, the pLCA open problems and the patent analysis approaches, methods and tools have been manually compared in order to suggest the most suitable ones to solve them among the seconds.

The manual matching has been carried out by redefining the open problems in an abstract way with respect to the pLCA context and linking them only to the tasks of technological forecasting and information retrieval. In this way, open problems no longer concern the definition of the functional unit and the construction of the inventory, but exclusively the extraction of information relating to the inventions presented in the patents. In this way, manual matching exclusively concerns the search for certain patent analysis approaches, methods and tools, among the reference literature, to support the extraction of information from patents. Following the reformulation of open problems, which in our opinion is better performed manually, the matching could be automated in the future, for example using the natural language process of the literature about patent analysis.

Fig. 1 schematizes the methodology used to retrieve, from the scientific literature, and match pLCA open problems and possible solutions related to patent analysis.

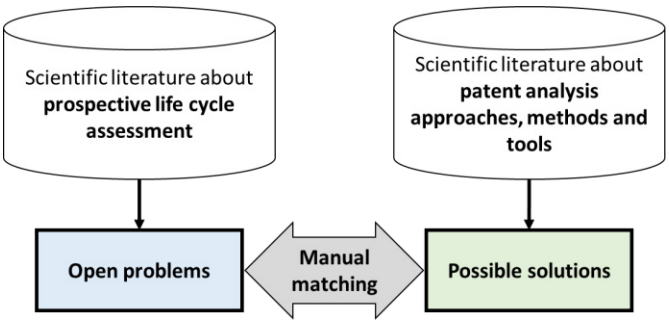

Fig. 1. The used methodology.

3. Results

In the following sections, the open problems of the pLCA, extracted from the literature, are explained in detail. For each of them, the possible uses of patent analysis, also extrapolated from the literature, which can support the pLCA by answering these problems, are reported and explained.

3.1. How to make technological forecasting less time-consuming?

A commonly used practice in pLCA for technological forecasting consists in extrapolating from considerations and scientific literature and proposing them to industry experts for scale-up procedure [15][19].

This activity is very time and cost consuming both in the process of selecting experts who are truly competent on the product and its future development and in preparing and conducting interviews with the experts [20].

In fact, it is essential to avoid considering possible future developments claimed as promising for the scientific community, but with little industrial interest [21].

In this context, the use of patents as a replacement for papers could streamline the scale-up procedure and the involvement of experts, reducing the number of solutions to be evaluated. This because the patents are expected to reflect production processes that are feasible and of high economic relevance, compared to papers whose purpose is to disseminate the results of scientific experimentation, beyond its industrial development [22]. In fact, for this same reason, some studies aimed at carrying out technological forecasting of different systems have provided different results when bibliometric analyzes of papers and patents have been carried out. For example, in [23] the laser is identified as the most advanced technology for carrying out tire pyrolysis in the papers, in terms of number of publications and citations, while the patents were instead more cautious in venturing into this solution, as regards the distribution of the publications.

Furthermore, to further limit the number of documents to be analyzed, the most widespread patent databases (e.g., Espacenet) allow patents to be selected based on the applicant. In this way it is possible to isolate the patents of the most reliable companies, whose technologies have a greater chance of being developed in the near future. This can be useful especially in highly monopolistic markets, where there are many players who patent and few who develop the technologies, possibly also acquiring the patents of other companies [24].

A typical criterion adopted in various pLCA studies for the selection of scientific articles relating to the future developments of a technology is the authoritativeness of the source, also evaluated based on the number of citations (e.g., [25][26]). However, this criterion is not sufficient, since a paper can be highly cited by other papers because it arouses interest from a scientific point of view, not necessarily from an industrial development point of view [21].

On the other hand, the analysis of the maintenance costs of a patent can be considered an index of how strategic the company that holds the patent itself considers its future development [27]. However, this analysis alone cannot be considered reliable. In fact, there are companies that keep a patent alive only to block any competitors from developing what they claim and not to develop it. Appropriate techniques to unmask patent blocking must therefore be considered in the analysis [28].

3.2. How to define the scenario range?

Arvidsson et al., [8] identified two main strategies to model the future foreground production system and scale in pLCA: predictive scenario that illustrate environmental impacts given some likely development and scenario range that are employed to illustrate the potential environmental impact, including extreme scenarios.

In the LCA literature there are no guidelines that support the definition of the ranges of values relating to a parameter or a function, to be associated with the data in the prospective inventory. From now on, for greater simplicity we will call these intervals of values "range".

To support the definition of the range, patents can be useful, since, unlike papers, they usually report the result across a range. The reason is in the different purpose: the articles aim to disclose a result, the patents to protect it, keeping it as hidden as possible from competitors. The use of the range must in any case be truthful for the examiner, for it to be granted in the patent.

In this regard, Butriy [9], with a systematic analysis of patent literature, drew the following conclusions on ranges in patents. (1) The ranges are instructions, qualitatively justified in the text of the patent itself both at a technical and industrial strategy level, rather than real experimental results on the prototype. (2) In case of asymmetric ranges with respect to the claimed value, the interpretation of the extremes changes. Typically, the closest is an already obtained experimental result while the furthest is a prospective result. (3) The ranges, to be accepted by the examiner, are usually defined according to the discipline to which the invention refers, not the characteristics of the invention itself.

Therefore, with such considerations, the ranges in patents could support the definition of the range scenario in the pLCA, enriching it with prospective considerations on certain strategic industrial interests related to product/process development.

3.3. How to support the background and foreground systems modelling?

In short, in the pLCA inventory, the system is modeled in two ways. The background system contains the elements on which the designer cannot intervene through the future development of the product, but which may evolve in the future; the foreground system instead contains the elements on which the designer can intervene.

In the prospective inventory, background data is collected from databases and their future evolution is modeled through macroeconomic simulations (for example, the forecast of banning a specific energy source, or a new European standard).

The foreground data are obtained by simulating the results that the designer aims to obtain in the future steps by new intervening on the product or process. Therefore, directly defining the boundary between the foreground system and the background system is fundamental to avoid ambiguity in the analysis and guarantee its significance of the implementation of product or process eco-design [29].

To support the identification of the foreground system, Tillman [30] stated that its boundaries coincide with those of the eco-design problem space developed starting from the pLCA results. In this way, the problem is shifted to the search for approaches for the formulation of the problem space.

In scientific literature, some authors have proposed methods to analyze patents to define the problem space. For example, the method of Liu et al. [31] isolates a pool of patents relating to the product and uses text mining to extract the requirements of itself product and its life cycle to improve the environmental sustainability. This is done by isolating all solutions in patents

that explicitly claim to improve sustainability or a related aspect, such as reducing energy consumption.

3.4. How to compare the future diffusion of a mature and an emerging technology?

Many pLCA studies create projections on the future diffusion of a mature technology that has been present on the market for some time, by analyzing historical series relating to its commercial diffusion and extrapolating a forecast regarding its future diffusion [32][33].

This method cannot be used to estimate the future evolution of an emerging technology with the same reliability because historical market data are not available. However, the time parameter is a fundamental requirement to carry out the comparison between different systems in the pLCA [21].

In this case, it is possible to compare projections on the future diffusion of mature technology and competing emerging technology through the analysis of their patent publication trends. In this way, the past time period available to carry out the analysis of emerging technology increases significantly compared to that of the analysis of the commercial time series and can be comparable with that of the analysis of the patent publication trend of mature technology [27].

Furthermore, some studies and research have shown that the analysis of the patent publication trend of a mature technology can be more reliable than the analysis of historical commercial data to predict the achievement of technological maturity [34].

3.5. How to support projections based on pathways to reach policy reductions to ensure time consistency?

Several pLCA studies use projections based on pathways to reach policy reductions, such as the Paris agreement [21]. This strategy is certainly useful, since product innovation is guided by reduction targets, even if this evidence manifests with variable times depending on the product, the reduction target, the political and geographical situation [35][36].

However, to use a projection based on pathways to reach policy reductions in pLCA, it is essential to recover a clear idea of the time interval to guarantee the time consistency of the analysis.

In this regard, the analysis of patent trends can enrich the projections based on pathways to achieve policy reductions with temporal considerations, given the correlations between the two aspects [37][38][39].

What these studies have in common is the analysis of patent trends as a tool for linking industrial innovation and the introduction of certain regulations about reduction targets. However, the analysis of the different cases, shows how the different relationships between the different aspects have emerged as a function of different factors including the type of the product and the geopolitical situation.

3.6. Final overview

To highlight the innovative aspects proposed by this research, the different open problems and possible solutions are summarized in Table 1.

Table 1. pLCA open problems and possible solutions related to patent analysis.

pLCA open problems	**Possible solutions related to patent analysis**
How to make technological forecasting less time-consuming?	Identifying in the patents the solutions that are considered most interesting by companies for future development through the selection of the applicant and the analysis of patent maintenance costs
How to define the scenario range?	Using and interpreting the ranges with which the results are presented in the patents
How to support the background and foreground systems modelling?	Using patents to identify the problem space, i.e., the foreground system, which is the most strategic in which to intervene during the eco-design of a technology
How to compare the future diffusion of a mature and an emerging technology?	The patent publication trends of mature and emerging technology are compared instead of the analysis of the historical series of commercial data
How to support projections based on pathways to reach policy reductions to ensure time consistency?	Using patent trends as time evidence of industrial innovation driven by reduction targets

4. Discussion and conclusions

The more general result of this study highlighted how the analysis of large amounts of patents can support pLCA in various aspects, currently considered critical.

However, from the comparison between the open problems moved by the pLCA community and the solutions provided, albeit indirectly by the patent analysis community, two limitations emerge that need to be filled to build a construction intersection between the two areas. In the following, these limitations are described and discussed in detail, referring to the hypothetical construction of a pragmatic patent analysis approach to support the pLCA. Furthermore, possible future developments are presented to achieve this aim.

4.1. Lack of subordination of the patent analysis to the quality requirements of the pLCA

The proposals of the literature that proposing patent analysis approaches, methods and tools have been compared to the open problems of the pLCA community by the authors, although they were obviously not conceived for this purpose. This discrepancy is especially noticeable if the patent analysis methods proposed are analyzed in light of the regulations governing the LCA, e.g., ISO 14040 e ISO 14044.

Satisfying these quality requirements, to rigorously solving the various problems with patent analysis, means subjecting the proposed methods and the obtainable results to a non-trivial review process. In fact, patent data are not always reliable for various reasons.

Review processes can significantly modify patent applications, for example by eliminating parts and reducing the claimed ranges. Patents obtained in certain states, e.g., China, are not considered as reliable as those of others, due to the less rigorous reviews of the various patent offices. Certain patents are filed only to block competitors, and therefore do not demonstrate an industrial trend towards a specific innovation in the future. However, many of the patent analysis approaches present in the literature do not consider these aspects, especially when large amounts of data are analyzed.

In this context, [14] proposes a patent analysis method in support of the pLCA and subordinated to satisfying the data quality requirements of the LCA. However, the scope of application is limited only to the extraction of foreground data for prospective inventory.

Therefore, for patents to truly be used reliably to support broad-spectrum the pLCA in all the ways presented in this study, it is necessary to establish new rules within which to conduct the different types of patent analyses.

4.2. The different types of patent analysis are unrelated, and a supporting tool is lacking

Although, in this study, different solutions or possible solution were provided for each open problem, a perfect matching between an open pLCA problem and a patent analysis method has never been identified.

To adequately respond to the problems, and also guaranteeing the data quality requirements of the LCA methodology, is preferable to combine the results obtained from the different patent analysis methods and not limit oneself to the analysis of patents alone.

For example, joint analyzes of scientific literature and patents can be useful to highlight temporal discrepancies in trends, to evaluate the time consistency of the analysis more carefully (e.g., Spreafico et al., [23]). Combining the analysis of patent maintenance costs with other analyzes on the financial state of the industries allows us to draw more robust hypotheses on the real development capacity of what is claimed in a patent by the industry that holds it [27].

Some implementation strategies for patent analysis to support pLCA are possible and can be developed in the future. Certain functionalities of common patent databases (Espacenet and Orbit by Questel) can be used to automatically filter the patents to increase the reliability and time and geographical consistency of the analysis [14]. The same databases and other commercial tools can be used to support patent bibliometrics, e.g., to analyze patent trends, and patent costs analysis, to identify the technologies under development that industries consider most strategic. Other tools can be used to compare technological trends extracted patent bibliometrics from other sources, such as social networks [40].

Natural language process techniques can be used for content analysis for different purposes. Rule-based techniques can be used to automatize the extraction of numerical values from patents to support the foreground inventory. While, other techniques can be used for automatically extracting unknown functions [31] of novel technologies from patents to better define the functional unit in pLCA.

Therefore, the only systematic patent search methodology to support the pLCA [14] which is limited to the construction of the foreground inventory could therefore be integrated with new implementations. Anyway, to develop implementations that offer reliable results for the pLCA, an analysis of them according to ISO 14040 and ISO 14044 requirements is necessary.

References

[1] Hetherington AC, Borrion AL, Griffiths OG, & McManus MC. Use of LCA as a development tool within early research: Challenges and issues across different sectors. International Journal of Life Cycle Assessment, 19(1), 2014. p. 130–143.

[2] ISO. 14040:2006. Environmental Management - LCA - Principles and Framework. 2006a.

[3] ISO. 14044:2006 Environmental Management - LCA - Requirements and Guidelines. 2006b

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

[5] Beltran AM, Cox B, Mutel C, van Vuuren DP, Vivanco DF, Deetman S, ... & Tukker A. When the background matters: using scenarios from integrated assessment models in prospective LCA. J. Ind. Ecol. submitted. 2018.

[6] Weidner T, Tulus V, & Guillén-Gosálbez G. Environmental sustainability assessment of large-scale hydrogen production using prospective life cycle analysis. international journal of hydrogen energy, 48(22); 2023. P. 8310-8327.

[7] Adrianto LR, van der Hulst MK, Tokaya JP, Arvidsson R, Blanco CF, Caldeira C, ... & Hauck M. 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); 2021. P. 1541-1544

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

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

[10] Peters J, Buchholz D, Passerini S, & Weil M. Life cycle assessment of sodium-ion batteries. Energy & Environmental Science, 9(5); 2016. P. 1744-1751.

[11] Miller D, Armstrong K, & Styring P. Assessing methods for the production of renewable benzene. Sustainable Production and Consumption, 32; 2022. P. 184-197.

[12] Karp SG, Schmitt CC, Moreira R, de Oliveira Penha R, de Mello AF. M., Herrmann LW, & Soccol CR. Sugarcane biorefineries: Status and perspectives in bioeconomy. BioEnergy Research, 15(4); 2022. P. 1842-1853.

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

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

[15] Yuan X, & Cai Y. Forecasting the development trend of low emission vehicle technologies: Based on patent data. Technological Forecasting and Social Change, 166, 120651; 2021.

[16] Daim T, Lai KK., Yalcin H, Alsoubie F, & Kumar V. Forecasting technological positioning through technology knowledge redundancy: Patent citation analysis of IoT, cybersecurity, and Blockchain. Technological Forecasting and Social Change, 161, 120329; 2020.
[17] Parteka A, & Kordalska A. Artificial intelligence and productivity: global evidence from AI patent and bibliometric data. Technovation, 125, 102764; 2023.
[18] Ai L, Ng SF, & Ong WJ. A prospective life cycle assessment of electrochemical CO2 reduction to selective formic acid and ethylene. ChemSusChem, 15(19), e202200857. 2022.
[19] Sun Y, Bai S, Wang X, Ren N, & You S. Prospective life cycle assessment for the electrochemical oxidation wastewater treatment process: From laboratory to industrial scale. Environmental Science & Technology, 57(3); 2023. P. 1456-1466.
[20] Rückert P, Khabipova A, & Tracht K. Development of a Sustainability Strategy for Fuel Cells Using Life Cycle Analysis and Expert Interviews. In Global Conference on Sustainable Manufacturing (pp. 892-900). Cham: Springer International Publishing. 2022.
[21] Bruhn S, Sacchi R, Cimpan C, & Birkved M. Ten questions concerning prospective LCA for decision support for the built environment. Building and Environment, 110535; 2023.
[22] Jaffe AB, & Trajtenberg M. Patents, citations, and innovations: A window on the knowledge economy. MIT press. 2002.
[23] Spreafico C, Russo D, & Spreafico M. Investigating the evolution of pyrolysis technologies through bibliometric analysis of patents and papers. Journal of Analytical and Applied Pyrolysis, 159, 105021. 2021.
[24] Li S, Zhang X, Xu H, Fang S, Garces E, & Daim T. Measuring strategic technological strength: patent portfolio model. Technological Forecasting and Social Change, 157, 120119. 2020.
[25] Ramon D, & Allacker K. Integrating long term temporal changes in the Belgian electricity mix in environmental attributional life cycle assessment of buildings. Journal of Cleaner Production, 297, 126624. 2021.
[26] Ambrose H, & Kendall A. Understanding the future of lithium: Part 2, temporally and spatially resolved life‐cycle assessment modeling. Journal of Industrial Ecology, 24(1), 2020. P. 90-100.
[27] Russo D, Spreafico M, & Spreafico C. Supporting decision making in design creativity through requirements identification and evaluation. International Journal of Design Creativity and Innovation; 2023. P. 1-17.
[28] Corsino M, Mariani M, & Torrisi S. Firm strategic behavior and the measurement of knowledge flows with patent citations. Strategic Management Journal, 40(7); 2019. P. 1040-1069
[29] Mori M, Iribarren D, Cren, J, Cor E, Lotrič A, Gramc J., ... & Dufour J. Life cycle sustainability assessment of a proton exchange membrane fuel cell technology for ecodesign purposes. International Journal of Hydrogen Energy; 2023.
[30] Tillman AM. Significance of decision-making for LCA methodology. Environmental impact assessment review, 20(1); 2000. P. 113-123.
[31] Liu L, Li Y, Xiong Y, & Cavallucci D. A new function-based patent knowledge retrieval tool for conceptual design of innovative products. Computers in Industry, 115. 103154. 2020.
[32] Löbberding H, Wessel S., Offermanns C, Kehrer M, Rother J, Heimes H, & Kampker A. From cell to battery system in BEVs: Analysis of system packing efficiency and cell types. World Electric Vehicle Journal, 11(4), 77. 2020.
[33] Meindl M, de Ruiter C, Marciello V, Stasio MD, Hilpert F, Ruocco M, ... & Maerz M. Decarbonised Future Regional Airport Infrastructure. Aerospace, 10(3): 2023. P. 283. 2023.
[34] Adamuthe AC, & Thampi GT. Technology forecasting: A case study of computational technologies. Technological forecasting and social change, 143; 2019. P. 181-189.
[35] Shen F, Liu B, Luo F, Wu C, Chen H, & Wei W. The effect of economic growth target constraints on green technology innovation. Journal of environmental management, 292, 112765. 2021.
[36] Mitrano DM, & Wohlleben W. Microplastic regulation should be more precise to incentivize both innovation and environmental safety. Nature communications, 11(1), 5324. 2020.
[37] Mbanyele W, & Wang F. Environmental regulation and technological innovation: Evidence from China. Environmental Science and Pollution Research, 29(9), 12890-12910. 2022.
[38] Nie X, Wu J, Zhang W, Zhang J, Wang W, Wang Y., ... & Wang H. Can environmental regulation promote urban innovation in the underdeveloped coastal regions of western China?. Marine Policy, 133, 104709. 2021.
[39] Lv C, Shao C, & Lee CC. Green technology innovation and financial development: Do environmental regulation and innovation output matter?. Energy Economics, 98, 105237. 2021.
[40] Li S, Garces E, & Daim T. Technology forecasting by analogy-based on social network analysis: The case of autonomous vehicles. Technological Forecasting and Social Change, 148, 119731. 2019.