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Exploring Technology Evolution Pathways to Facilitate Technology Management: From a Technology Life Cycle Perspective

Ying Huang[a,b*], Fujin Zhu[c,d], Alan L. Porter[e,f], Yi Zhang[d], Donghua Zhu[c], Ying Guo[g,*]

[a] School of Information Management, Wuhan University, Wuhan 430072, China

[b] Department MSI, Centre for R&D Monitoring (ECOOM), KU Leuven, Leuven 3000, Belgium

[c] School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China

[d] Centre for Artificial Intelligence, Faculty of Engineering and Information Technology, University of Technology Sydney, NSW 2007, Australia

[e] Search Technology, Inc., Norcross, GA 30092, United States

[f] Program in Science, Technology & Innovation Policy (STIP), Georgia Institute of Technology, Atlanta, GA 30332, United States

[g] Business School, China University of Political Science and Law, Beijing 100088, China

Corresponding Email: huangying_work@126.com (Ying HUANG); guoying_bit@163.com (Ying GUO)

ABSTRACT

Technological innovation is a dynamic process that spans the lifecycle of an idea, from scientific research to production. Within this process, there are few key innovations that significantly impact a technology's development, and the ability to identify and trace the development of these key innovations comes with a great payoff for researchers and technology managers. In this paper, we present a framework for identifying the technology's main evolutionary pathway of a technology. What is unique about this framework is that we introduce new indicators that reflect the connectivity and the modularity in the interior citation network to distinguish between the stages of a technology's development. We also show how information about a family of patents can be used to build a comprehensive patent citation network. Last, we apply integrated approaches of main path analysis (MPA) -- namely global main path analysis and global key-route main analysis -- for extracting technological trajectories at different technological stages. We illustrate this approach with Dye-Sensitized Solar Cells (DSSCs), a low-cost solar cell belonging to the group of thin film solar cells, contributing to the remarkable growth in the renewable energy industry. The results show how this approach can trace the main development trajectory of a research field and distinguish key technologies to help decision-makers manage the technological stages of their innovation processes more effectively.

Index Terms—Tech mining; technology evolution pathway; patent citation network; main path analysis (MPA); Dye-Sensitized Solar Cells (DSSCs)

I. INTRODUCTION

Different technologies can play different roles at different stages of research and development. The core and emerging technologies are essential to science and technology planning and formulating R&D strategies [1], According to studies on technological opportunity [2, 3], identifying the core and emerging technologies in a field, tracing their history, and monitoring current their current progress is vital to recognizing the best opportunities and capitalizing on them before the rest of the market catches on.

Many researchers have attempted to identify technology structures and trace technological trends through patent analysis [4-8]. The earliest approaches were mostly simple longitudinal comparisons of the number of patents assigned to different regions, assignees, inventors, technology categories, etc. [9-12]. Yet quantity is a rudimentary indicator that cannot reflect micro-level changes in the evolution of a technology. For this reason, patent citations emerged as an important indicator of how technologies develop over time. A patent citation signifies a technological relationship between two inventions: one drawing inspiration or componentry from another [13]. Hence, citations provide a reasonable "proxy" for technological significance, and, generally, they appear to be highly correlated with other measures for quantifying innovation [14]. Patent citation networks can be understood as a representation of the relationships among the pieces of knowledge in individual patents. From this perspective, they are maps of the "technological trajectories" in a given technology arena. In vast citation networks, it is common to find that some patents have played a notable role in that technology's progression. Almost inevitably, these patents represent the key technologies in the field and are usually located on a "main trajectory" in the citation network. By identifying these patents, one can gain insight into the main advancements in a specific technology [15].

There are several methods for identifying citation trajectories and analyzing a technology's evolution, one being main path analysis (MPA), which was introduced by Hummon and Doreian [16]. MPA typically yields fruitful considerations and findings, but it has three notable MPA limitations that need to be addressed.

First, the evolution of technology often follows a complex set of pathways, and the different stages of a technology's lifecycle tend to show different characteristics. Therefore, when developing an R&D strategy, it is vital to consider the full life cycle of a technology. A complete and well-rounded picture of a TLC would capture the most pertinent characteristics of how a target technology has changed over time as a way to provide insight into its germination, growth, maturity, and recession. Hence, TLCs can be thought of as collections of period patterns that build to reveal the entire evolution of a technology [17].

Second, most of these analyses ignore the essential role of patent families when constructing citation networks. Consolidating data into patent families not only helps to reduce duplication in the data, but it also helps to highlight less overt information, such as the geographic center of the patentee, the significance patentees place on particular patents, and so on [18]. Our search did not reveal much literature on using MPA with patent families. Some scholars have noted the importance of including patent family information when analyzing a single applicant's patent portfolio; however, their studies are limited to investigating the members of only one patent family [19, 20]. The use of multiple authorities' patent data bundled with the patent family information can significantly improve the coverage and practicability of patent citation analysis [21].

Third, most of MPAs either offers a complex "network of main paths," or one and only the most significant development path. However, for a large citation network, the "network of main paths" does not achieve the goal of simplifying the citation network. As mentioned, the influence of particular advancements can change dramatically through the full lifecycle of a technology. In turn, the impact of citations needs to be considered in the same context – at the stage of life they were given. Undertaking several 'mini-MPAs' over citation networks at different points of time would show different technological trajectories that need to be understood to properly explore the process of knowledge diffusion.

Thus, in this paper, we present a systematic approach to tracing and analyzing the main pathways of a technology's evolution. Our approach takes four forms of intelligence into consideration, as follows.

1) To identify the Technology Life Cycle (TLC) stage, by introducing an indicator of connectivity and modularity in the interior citation network;
2) To use patent family data, rather than individual patents, when building a citation network to fully represent all citation relationships and characteristics.
3) To apply integrated MPA to construct a set of technology trajectories and then trace the technology evolution pathways at each stage.

The remainder of this article is organized as follows. Following this introduction, a short overview of related literature is provided in Section 2. Section 3 describes the framework and main methods applied in our study, including the process of analyzing TLCs and identifying patent evolution pathways. Section 4 presents a case study application of the suggested approach using Dye-Sensitized Solar Cells (DSSCs) as the subject technology. Finally, in Section 5, we conclude with the summary, discussion, and further research ideas.

II. RELATED LITERATURE

A. Technology life cycle

The concept of the TLC is an extension of the now-familiar product life cycle (PLC) models that date back to the 1960s [22]. In 1981, Ford and Ryan proposed a conceptual standard that reveals the base level of technological development to the application level of different technologies [23]. And, in the same year, analysts at the firm of Arthur D. Little [24] developed a TLC model that represents the evolution of the technologies with a system similar to one used to reveal the life cycle of an industry. Among the various TLC-related models, the S-curve connects investment in technology to observe technological performance, either overtime or in terms of cumulative R&D expenditures.

It is generally accepted that TLC includes two dimensions: 1) competitive impact and 2) integration in products or processes, which can be divided into four stages with different characteristics—emerging, growth, maturity, and decline [25]. Most S-curve approaches are mainly based on measuring the change in individual indicators to construct evolutionary trajectories, e.g., the number of patents granted or the rate of patent growth, while overlooking the connections and flows of knowledge among topics [26]. However, the single indicator can only show part of the characteristics of the TLC, which may lead to deviations in the judgment of the TLC due to lack of information. Therefore, more and more researchers tend to introduce multiple indicators to measure and locate TLC ([26-31]. Though such statistical indicators offer a convenient way to make sense of the technological stage, they ignore the technology nature of internal knowledge flows and overflows. In other words, traditional TLC methods cannot fully explain the dynamic mechanisms of a technology's evolution; they fail to determine inner representations.

B. Main path analysis (MPA)

Hummon and Doreian [16] called the sequence of links and nodes in a network *search paths* and calculated a "traversal count" for each link to quantify the connectivity. Identifying and analyzing the major search paths in a citation network is what we now call main path analysis (MPA). As a mathematical tool, MPA has become one of the most attractive methods of tracing technological trajectories, exploring scientific knowledge flows, and conducting literature reviews.

According to Hummon and Doreian [16], MPA modeling reveals the primary development trend in research fields by identifying paths of maximum connectivity from a series of studies in the literature. Over several studies, Hummon and his colleagues applied MPA to the centrality-productivity citation structures [32], to social network analysis [33], as well as to conflict-resolution [34]. MPA has also been extended using bibliographical citation data and/or patent citation data to: trace technological trajectories [35-37], highlight important references, investigate topics and methodologies in a field [38-40], provide insight into the co-evolution of scientific and technical knowledge [41], and show the structure and specific characteristics of knowledge diffusion processes [42, 43]. In addition, MPA has also been applied to find significant court opinions by taking citation relevancy into consideration [44].

III. FRAMEWORK AND METHOD

With this research, we offer a systematic approach to better-exploiting patent resources when attempting to identify technology evolution pathways as a way to provide competitive technical intelligence. The framework of our approach is illustrated in Fig. 1. For this process, we used professional text-mining software, *VantagePoint* (http://www.theVantage-Point.com), to help accomplish the text analyses and combining it with citation analyses.

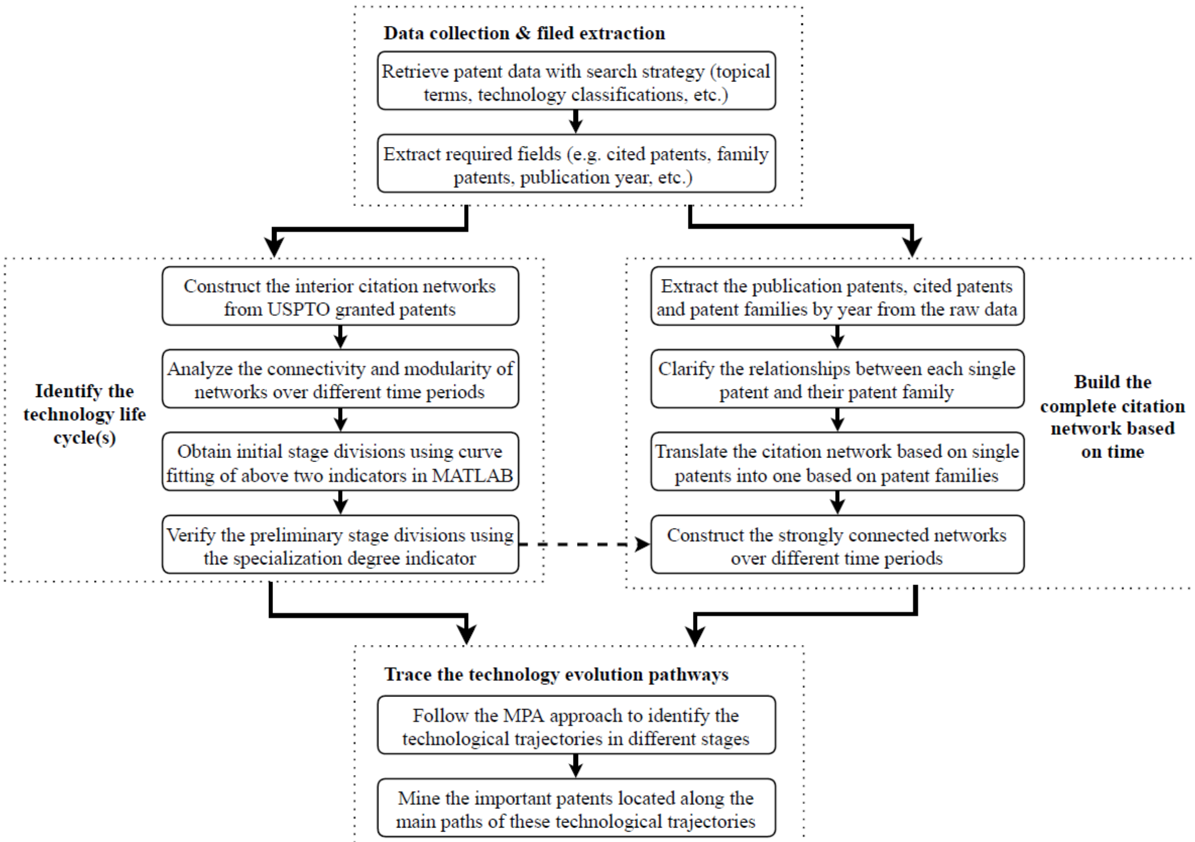


Fig. 1. Framework to explore technology evolution from the TLC perspective

A. Identifying the technology life cycle

The process of technology evolution can be interpreted through the evolution of patent citation behavior. This process is, to some extent, analogous to the progress of urbanization. For example, suppose that a node is an individual, and a link represents a relationship in a community. In the beginning, a city is a small, sparsely-populated village, where few have relationships. Then, as more people move to the village, closer relationships begin to develop. The population grows, and the community becomes even more connected even though many individuals remain isolated. The population keeps growing and eventually stabilizes, where strong relationships among particular individuals form a series of communities that can be merged into some larger components. The schematic diagram is presented in Fig. 2.

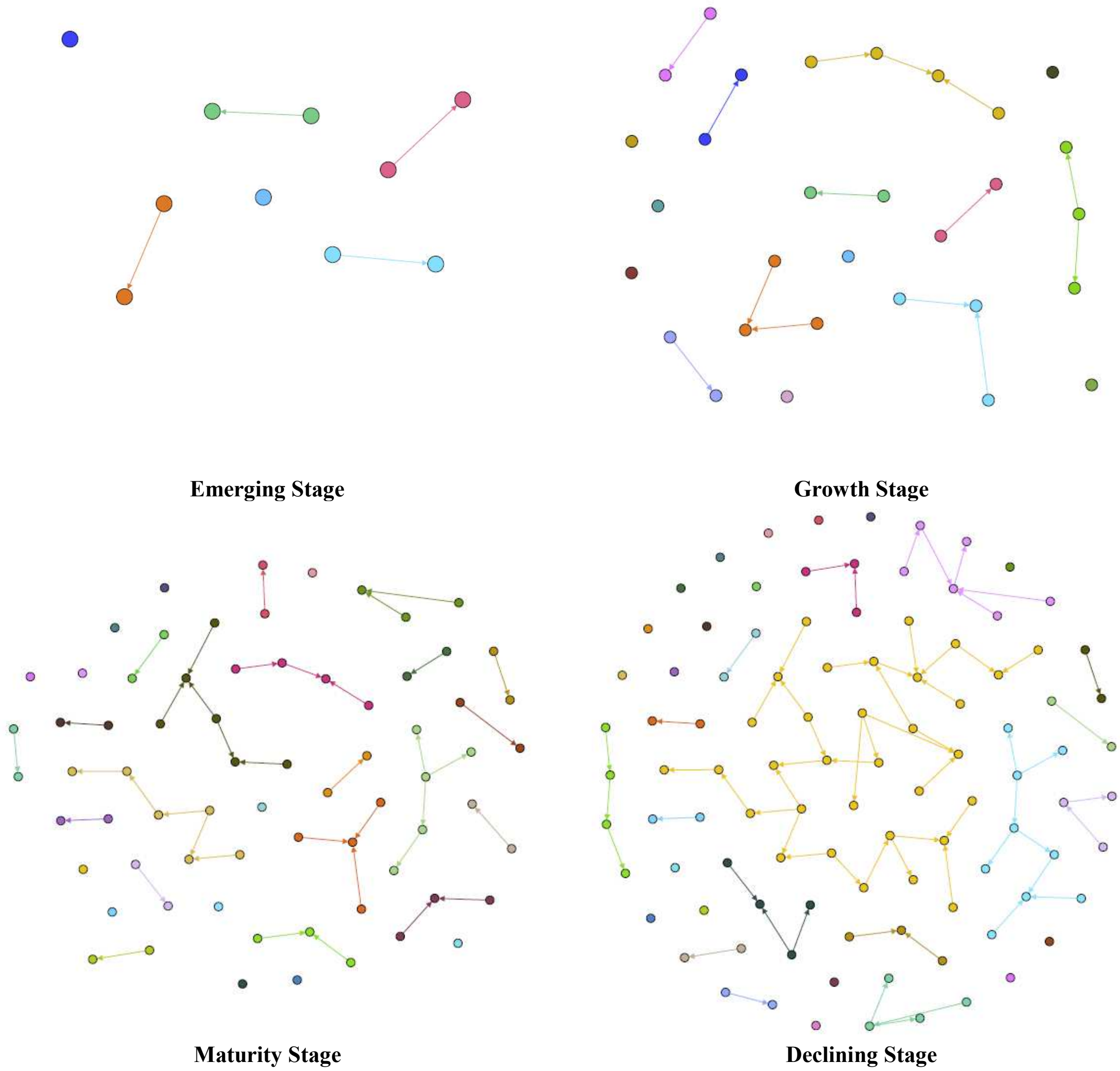


Fig. 2. Schematic diagram of community evolution over different life cycle periods

To describe these temporal processes, we introduce two concepts. The first is the growth rate of connected edges – called "arcs" in directed networks. The second is the growth rate of weakly-connected components, which can be used to observe the evolution of a technology over a period of development. Here, the arcs represent citation links, and the connected components are the linked communities in which all nodes are connected. The number of connected edges/arcs and the number of connected components accumulated year on year can be discovered with social network analysis tools, e.g., Pajek, UCINET, Gephi, etc. Once known, the two indicators can be charted in MATLAB (http://www.mathworks.com) so that the slope of the fitted curves reflects the growth characteristics of the citation network.

In general, when a certain new technology first appears, the rate of activity increases slowly during the emerging stage, and limited sub-technologies distributed separately and scatteredly. At the growth stage, the technology develops very fast, typically toward a focus that often appears as a closely-linked set of nodes. In the maturity stage, isolated independent communities begin to emerge as new connected communities and the number of nodes grows rapidly. In the decline stage, technology integration becomes the trend, and citation linkages also become more frequent and minor technological components tend to merge into larger technology communities. A summary of the characteristics of these TLC stages in relation to the growth rate of connected edges/arcs and weakly-connected components is provided in Table 1.

Table 1. The growth trends of citation network characteristics in different stages

Life cycle	The number of the of edges/arcs	The number of connected components
Emerging Stage	↑	↑
Growth Stage	↑↑	↑
Maturity Stage	↑	↑↑
Decline Stage	↑↑	↓

In addition to the characteristics of a citation network, the distribution of its technological fields also provides a basis for distinguishing its phases of evolution. In early stages, patents are typically distributed sporadically across a range of different fields, and a small number of assignees hold just a few relatively disparate patents. With the accelerated technological development, the growing patent application expend the distribution in technological fields. In fact, Leydesdorff et al. [45] observed a cyclical pattern in longitudinal readings of the Rao–Stirling diversity indicator over nine materials for photovoltaic cells, and they concluded that these cyclical patterns could be used as indicators for a technological life cycle. In other words, the changes in International Patent Classifications (IPCs) over time can be an indicator of the different stages of a technology's development. Supported by this finding, we argue that the level of technology specialization in a patent citation network can be used to verify our initial judgment of the TLC of a targeted technology. Porter et al. [46] originally proposed the specialization score to measure the extent to which a research outcome relates to a particular field of research. Then, it is employed to conduct patent specialization score analysis by using transformed IPCs rather than subject categories from Web of Science [47]. The specialization score is calculated with the following formula:

$$\mathrm{S} = \sum_{ij} f_{IPC_i} * f_{IPC_j} * COS(IPC_i, IPC_j)$$

Here, f_{IPC_i} and f_{IPC_j} are the proportions of elements assigned to the technological categories *i* and *j,* and $COS(IPC_i, IPC_j)$ is a measure of their similarity. Note that the categories *i* and *j* should roughly have the same number of elements each, as a great imbalance may lead to bias in favor of the larger category. We followed the research conducted by Leydesdorff and his colleagues [45], and took 630 IPC classes at the four-digit level as the benchmark for calculating the patent specialization score.

B. Constructing a complete citation network

Patent citation analysis is a common way to structure a large number of patents, to profile technology landscapes, and to capture knowledge transfer and change across technologies or industries. For ease and simplicity, many researchers draw their data from a single patenting authority. However, this means patent families cannot be included in the analysis. A patent family is a collection of closely-related patents derived from the same core technology but issued by authorities in different countries [48]. Therefore, this can be a useful information source because retrieving duplicate data can be avoided during a search of patents across patent authorities [49].

Citation behavior is different across patent authorities and also between parent and child patents, so global technology trends cannot be understood as well by analyzing just the patent data issued by a single authority. However, when drawing data from multiple authorities, it is important to merge patent documents from a family into a single-family record. Patent families are usually identified by the claim of priority or disclosure and, here, each patent family is denoted by the earliest published patent in the family. All cited members of a patent family are then merged to form the family record. Within and between patent families, there can be four types of links (citations), as shown in Fig. 3.

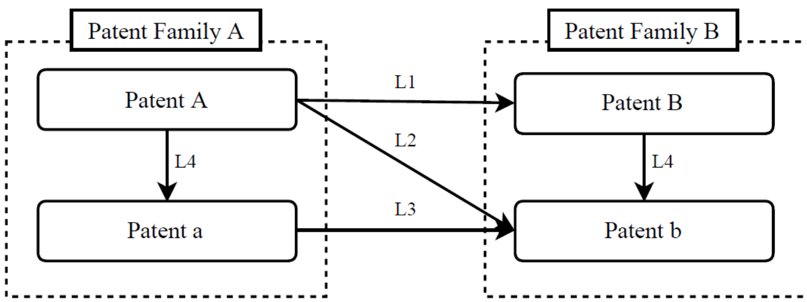


Fig. 3. The four types of links (citations) between and within patent families

Note: Patents A and B are parent patents from the first issuing authority. Patents a and b are child patents, i.e., the same patent issued by another authority.

In this example, consider two patent families: Family A and Family B, and the filing date of patent Family A is earlier than Family B. Each family includes one parent patent (typically the first non-provisional patent application filed for an invention) and one child patent (benefits from the priority date of the parent(s)). Therefore, the four different citation relationships that can occur between parents and children and between families are as follows. L1 is close to what we know as a standard citation where Patent B cites Patent A. Patent A can also be cited by Patent B's child, Patent b, which is L2. A child can cite a child, i.e., Patent b can cite Patent a as L3. Lastly, a child can cite its own parent, e.g., Patent a can cite Patent A – L4. Given that most studies draw from one patenting authority, most citation analysis only captures parent to parent citations (L1) and/or child to child citations (L3). The result may be fragmented network structures that do not present the full connections or diffusions among different technology topics. By considering patent families, our approach captures all four types of citations to provide a more comprehensive picture of the structure within and between inventions.

A general directed network consists of vertices and arcs that link two vertices (nodes). While conducting MPA for a given field of technology based on the patent citation network, we are more concerned about the citations between patents within that field, and these effective citations are extracted from the merged family records. In an acyclic citation network, in addition to the four types of citations, there are four types of vertices that correspond to the four different kinds of patent family records: 1) isolated records– the patent families that cite no other patents, and are not cited; 2) source records – patent families that cite no patents, but are cited; 3) sink records – patent families that cite others, but are not cited by others; and 4) intermediate records – patent families that both cite and are cited. To simplify the process of analyzing the technological trajectories and identifying core patents, we recommend disregarding orphans, i.e., the patents neither cite nor are cited by at least one patent, as these patents are digressions from the main technology.

C. Tracing the technology evolution pathway

In an acyclic directed network, the main path is the path from a source vertex to a sink vertex with the highest traversal weights on its arcs [50]. Hence, the two steps needed to identify the main path in an acyclic directed network are as follows:

1) Calculate the traversal weight by tracing each citation link from a set of starting vertices to the end vertex.
2) Trace the links that have the highest traversal weights to map out the most representative path in the network.

As the traversal weights are very sensitive to the network structure, how to measure them poses an important step in MPA. The most widespread algorithms/indices are Node Pair Projection Count (NPCC), Search Path Link Count (SPLC), and Search Path Nodes Pair (SPNP), all of which were proposed by Hummon and Doreian [16]. In 2003, Batagelj [51] proposed a new traversal count, namely Search Path Count (SPC), concluding that SPC performs a bit better than SPLC and SPNP (noting that these indices almost always produce the same results). Later, Choi and Park [2] suggested a Forward Citation Node Pair (FCNP) to distinguish patent development paths from a large patent citation network by evaluating the weight of citations among patents.

Most studies in the application-oriented literature simply adopt SPLC, SPNP, or SPC without detailing a rationale for their choice. Liu, Lu and Ho [52] made an attempt to clarify the differences between SPLC, SPNP, and SPC through a messenger and tollway analogy. Ultimately, they endorsed SPLC as the preferred choice for traversal weight because, vastly summarizing their detailed discussion, it describes knowledge diffusion scenarios in science and technology development better than the other traversal weights. Hence, we have followed their recommendations and applied SPLC throughout.

Once the SPLC weight of each node is established, an algorithm needs to calculate the main trajectory for each of the different stages and then concatenate those trajectories into the final technology evolution pathway. Most traditional algorithms take a "local" approach, in that they start at a node and hop through the links with the highest traversal counts. This approach highlights significance at a particular point in time and tracks the most significant citation link at every possible splitting point. Alternatively, a global algorithm delivers the path with the largest overall traversal count even if some nodes along the path may be relatively insignificant [53]. In other words, local main paths tend to highlight significant leaps in progress, while global main paths tends to emphasize the significant overall knowledge flows [54]. Fig. 4 illustrates these different approaches of main path analysis.

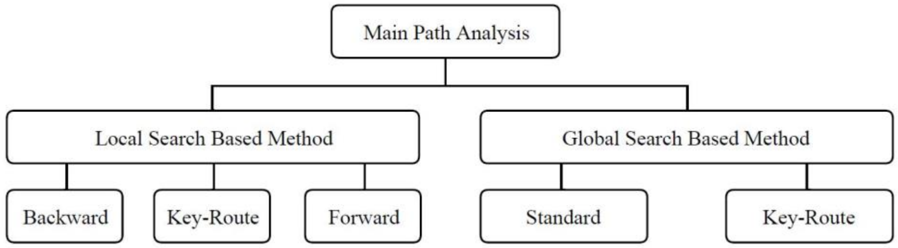


Fig. 4. Main methods of seeking for the main path in MPA

It is worth noting that both the previous local search-based method (forward and backward) and the global search-based method (standard) may overlook the links with the highest traversal counts. Hence, Liu et al. [39, 54] introduced a new method called *key-route* to enhance MPA by adding an algorithm to search for multiple paths and guarantee inclusion of the top links in these multiple paths. This approach viewed main path as an extension of a specific key route, and searched one or more main paths by first locating the arc(s) having the greatest weight and tracing both backward and forward until source and sink nodes are reached [55].

Our framework prescribes the global key-route MPA method applied to each of the different periods. The result is a comprehensive search of multiple paths to arrive at the path with the most significant overall traversal count over the technology's evolution. The procedure of the multiple global key-route method is as follows: 1) select the link that has the highest traversal count as the key-route; 2) utilize standard search to trace the nodes that have the largest overall traversal counts. The multiple global key-route method not only provides multiple paths, from which we can find the knowledge diffusion trajectory comprehensively, but also contains almost all the important connections and makes the results much more comprehensive.

The last steps are to analyze the patents along the main path once identified. For this, we apply the semiautomatic "term clumping" steps, which generate better term lists for achieving competitive technical intelligence by using enhanced bibliometric and text mining techniques [56].

IV. CASE STUDY AND RESULTS

To demonstrate our proposed approach, we selected DSSCs, an important nanoscience domain that has contributed to photovoltaic technology development, as our case study. DSSCs are not as reliant on highly pure materials as conventional silicon-based solar cells, and manufacturing costs are approximately halved, making DSSCs an attractive alternative [57].

We drew data from the Thomson Innovation patent compilation provided by Thomson Reuters (now, Clarivate). This is a comprehensive worldwide patent database system that covers patents issued by more than 80 authorities, including the Derwent World Patents Index (DWPI) patent data and the Derwent Patent Citation Index (DPCI). While not mandatory, DWPI allows claimants to declare their patent as a member of a certain family. The families are determined by experts based on the claim and their own investigations.

Over the past few years, we have used multiple search strategies to locate patents related to DSSCs for various studies, tuning the algorithm with every attempt. After repeated verification, the search query we favor is: ABD=((Dye* or Pigment*) and (Sensiti*) and (Solar* or Photovoltaic*) and (Cell* or Batter*)) [58]. From experience, we know that the first seminal paper on DSSCs was published in 1991 [59] and, therefore, the time span for this study is from 1991 to 2017. We conducted our search on 17 March 2019, limiting the period of study to two years prior to account for citation lag. The total number of patent families in the set was thus 8648.

The annual growth in DSSCs patents during 1991-2017 is presented in Fig. 5. There was a steady increase in the number of patents from 1991 to a peak in 2012, followed by a sudden and remarkable decline. The number of patents filed each year has continued to decrease ever since. This pattern is also reflected in the rate of growth, which shows an obvious fluctuation before 2001, followed by a fall into negative territory in 2013. Based on this trend, we can surmise that the number of new patents may continue to fall unless there are some significant breakthroughs in the field. We can also assume that many product-related technologies have been commercialized and that market competition is likely to intensify.

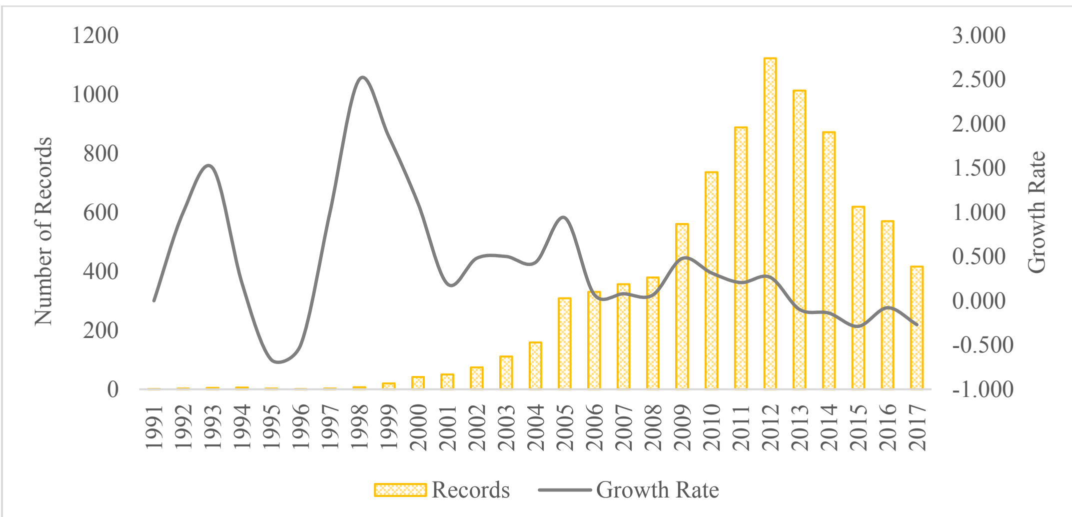
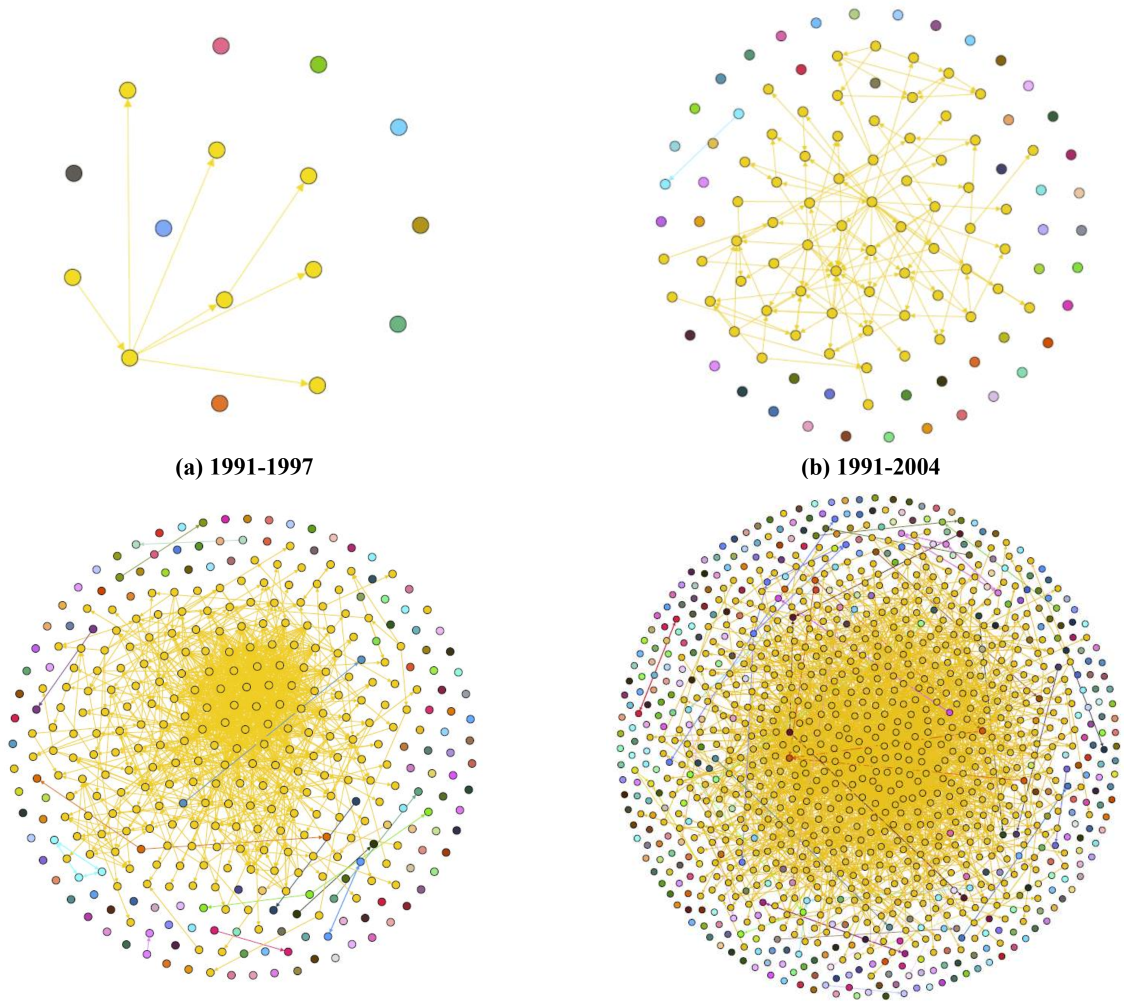


Fig. 5. The annual trend and growth rate of DSSCs patent during 1991-2017

To better highlight the actual innovations in DSSCs and decrease the influence of commercial activity, we temporarily distilled our corpus down to raw data from the USPTO. These patents provide integral citation information to identify the TLC of DSSCs for two reasons. First, patents granted by the USPTO come with complete citations and references, which is necessary for constructing a citation network. Second, the vast majority of important patents have global appeal, and, if an assignee intends to pursue business in the global market, they will almost certainly seek intellectual property protection from the USPTO. Hence, the patent application history provided by the USPTO is typically much more comprehensive than other patent offices. The USPTO provided 1140 granted patents, which we used to conduct the TLC analysis. Fixing 1991 as the starting year, we built a series of citation networks, adding data to each network a year at a time. With each new year of data, we calculated the number of arcs and components in the network. Snapshots of these networks at 1997, 2004, 2011, and 2017 are shown in Fig. 6, providing a glimpse into the significant developments in each time period. These maps were generated in Gephi (http://gephi.org/). The different colors indicate different components.



(a) 1991-1997 (b) 1991-2004

(c) 1991-2011 (d) 1991-2017

Fig. 6. Snapshots of the citation network for DSSCs patents granted by the USPTO over time

The fitting curves for these networks produced by MATLAB are shown in Fig. 7. In repeated tests, the growth trends of the connected edges and weakly-connected components coalesced into three curves representing three phases. The results show that, prior to the early 21st century, there were few DSSCs patents, most of which did not cite each other, and growth was slow. After 2002, the links between DSSCs patents became much more frequent, and discrete technology communities gradually formed. Upon entering the 2010s, new technology communities began to grow at rapid speeds, i.e., new and emerging technology focuses began to form and develop. Therefore, based on these results, the first three stages of DSSC's development are divided as follows: emerging (1991–2001), growth (2002–2011), and maturity (2012–2017).

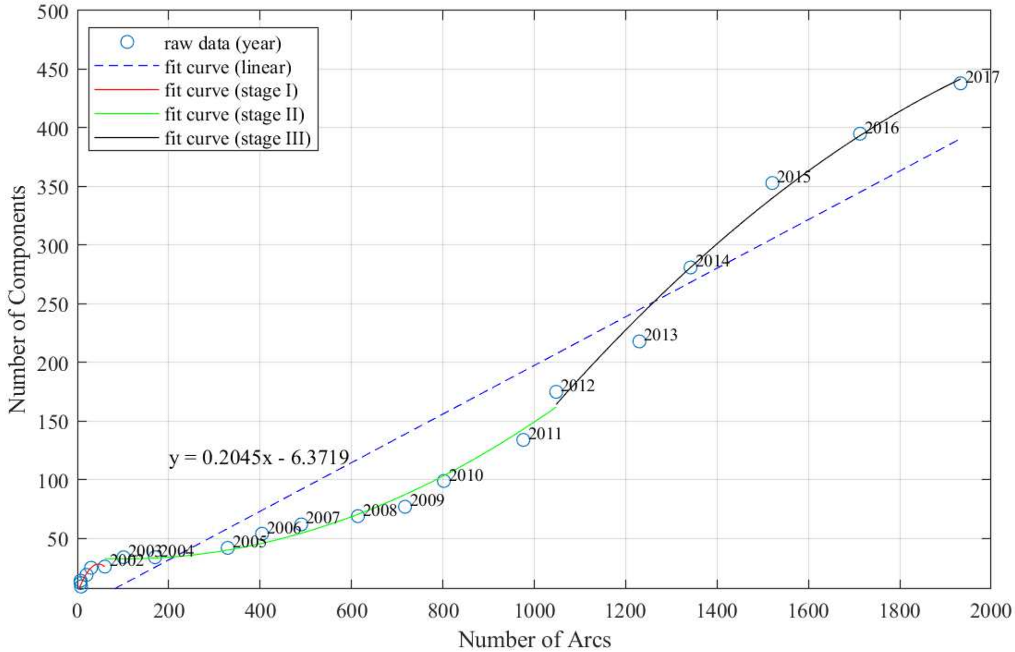


Fig. 7. The fitting curve of components and arcs in the DSSCs patent citation network

As stated, different technologies play different roles at different stages of a TLC, which the cyclical patterns in technology specialization can signal. Therefore, to verify our initial division of stages, we calculated specialization scores across the period. The results in Fig. 8 show obvious instability in the number of technology topics (IPC-4 categories) prior to 2001 but more stable fluctuations from 2002 onwards. This tells us that a technology revolution was taking place in several specific sub-technologies. After 2012, the number of IPC 4-digitals, aka IPC subclass, present an obvious increase. It is in this stage where we see DSSCs technologies being applied more broadly, and a boom in marginal patents or application-oriented patents at the same time.

Generally, in the early phases of a technology, there are only a few patents in very limited technology subfields. Additionally, inventors tend to participate in constructing a research frontier, while assignees are typically economic agents that sit outside a TLC to some extent [60]. The specialization results accord with these observations for the most part, which provides some endorsement of our initial stage divisions. To confirm our opinion, we showed our analysis to two DSSCs experts at the Georgia Institute of Technology. They confirmed that the results basically fit their understanding of the development of DSSCs. Overall, our analysis combined, with expert opinion, provides solid support for this approach as a reasonable way to set up further MPAs in different time periods.

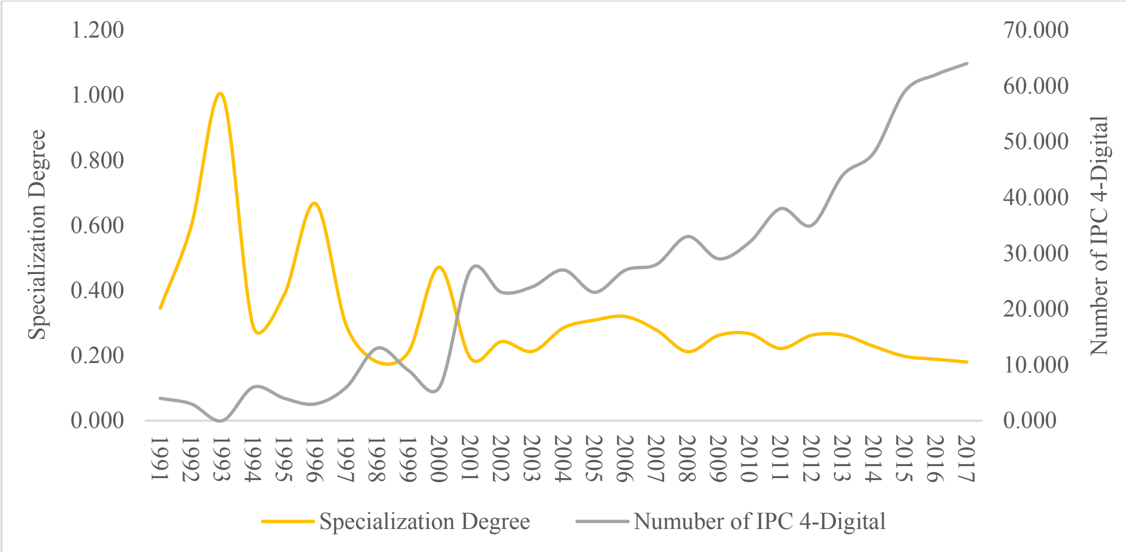
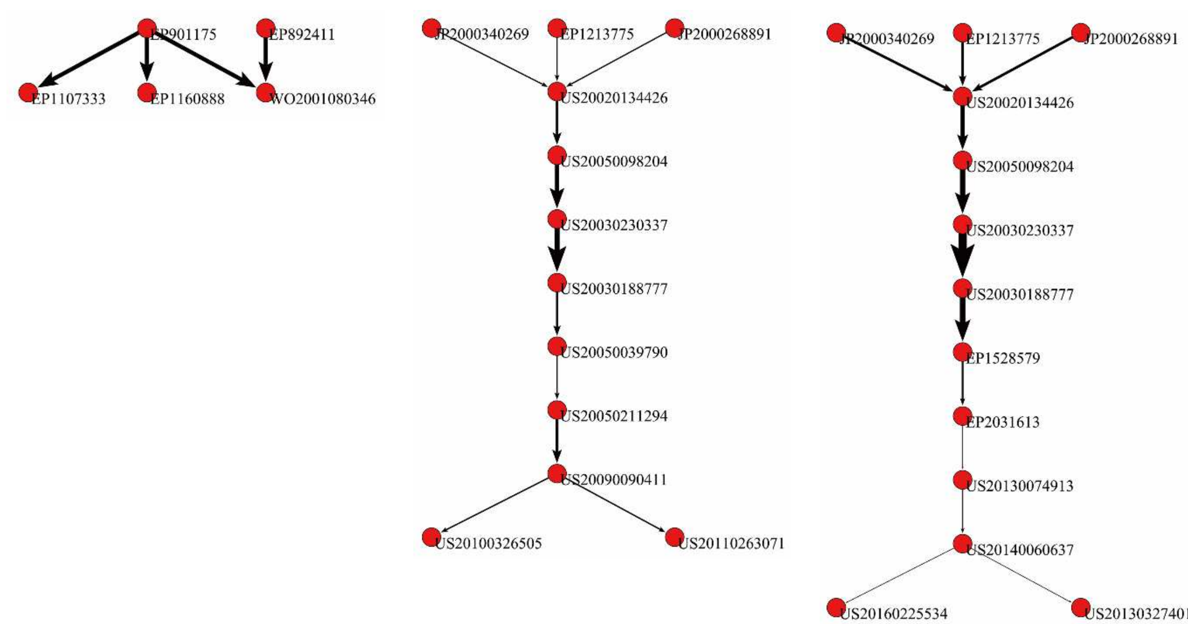


Fig. 8. The degree of technological specialization and the number of IPC 4-digital in DSSCs patent by year

The next stage of the analysis is to inspect the main pathways of evolution in each of the three phases, i.e., from the birth of DSSCs technology in 1991 to the end of the "emerging" TLC stage in 2001, then to the end of the growth stage in 2011, and through maturity up to the end of our study period in 2017. We used Pajek software (http://mrvar.fdv.uni-lj.si/pajek/) to extract and draw the main pathways by fixing 1991 as the starting year, while changing the ending year to 2001, 2011, 2017, as shown in Fig. 9. The thickness of an arc in a main path indicates the SPLC value of the citation it represents. Specifically, the thicker the arc, the higher the SPLC value.



(a) 1991-2001 **(b) 1991-2011** **(c) 1991-2017**

Fig. 9. Global standard main paths of DSSCs for three stages of the TLC

Fig. 9(a) contains five patents and four citation pairs. However, neither the patent nodes nor the citation pairs in the emerging stage remained prominent in the growth and maturity stages. One of the reasons is the sparsity of the citation network during this emerging period with only 138 patents and 7 citations across the entire decade to 2001. In contrast, there are significant overlaps between Figs. 9(b) and 9(c), with 7 patents located on both paths. JP2000268891, JP2000340269, and EP1213775 that is applied in 1999, 2000, and 2001 respectively, and four other patents (US20020134426, US20030188777, US20030230337, and US20050098204) are authorized / applied in the beginning of the growth stage. From these observations, we conclude that a significant overlap exists between global main paths of the growth stage and maturity stages. More detailed information about the patents located along this main technological trajectory is provided in Table 2.

Table 2. Details of the DSSCs patents in the main path with the global standard MPA approach

Publication Number	Application Year	Assignee	Main IPC	TLC stage		
				E	G	M
EP892411	1998	Fuji Film Corp	C09B-69/00; H01G-09/00; H01M-14/00	√		
EP901175	1998	Fuji Film Corp	H01L-51/00; H01M-14/00	√		
JP2000268891	1999	Toshiba Kk	H01L-31/00; H01M-14/00		√	√
EP1107333	2000	Fuji Film Corp	H01L-31/00; H01L-51/00	√		
EP1160888	2000	Sony Corp	C07C-217/00; H01L-29/00; H01L-31/00; H01L-51/00	√		
JP2000340269	2000	Showa Denko Kk	H01L-31/00; H01M-14/00		√	√
EP1213775	2001	Seiko Epson Corp	H01L-31/00; H01L-51/00		√	√
WO2001080346	2001	Hayashibara Seibutsu Kagaku	H01L-29/00; H01L-31/00; H01M-14/00	√		
US20020134426	2002	Sharp Kk	H01L-31/00; H01M-14/00		√	√
US20030188777	2003	Konarka Technologies Inc	H01L-31/00		√	√
US20030230337	2003	Konarka Technologies Inc; Merck Patent Gmbh	H01G-09/00; H01L-31/00; H01L-51/00; H01M-14/00		√	√
EP1528579	2004	Korea Inst Sci & Technology	B05D-05/00; H01G-09/00; H01L-31/00			√
US20050039790	2004	Konarka Technologies Inc	H01L-31/00		√	
US20050098204	2004	Nanosolar Inc	H01L-31/00; H01L-51/00		√	√
US20050211294	2005	Konarka Technologies Inc	H01L-31/00; H02N-06/00		√	
US20090090411	2007	Univ Kangnung Nat, ETC.	H01L-31/00		√	
EP2031613	2008	Korea Inst Sci & Technology	H01G-09/00; H01L-31/00; H01M-14/00			√
US20100326505	2009	LG Display Co Ltd	H01G-09/00;		√	
US20110263071	2010	Univ Nat Tsing-Hua	H01L-21/00; H01L-31/00		√	
US20130074913	2011	Univ Hong Kong Polytechnic	H01G-09/00; H01L-31/00			√
US20140060637	2012	Univ I-Shou	H01L-31/00			√
US20130327401	2013	Univ Nat Yunlin Sci & Technology	H01G-09/00			√
US20160225534	2016	Univ Nat Yunlin Sci & Technology	H01G-09/00			√

Note: The TLC stage -- E, G, and M stand for the stage of emerging, growth, and maturity, respectively.

Another observation is that the technological focus, indicated by the main IPC numbers of these patents, consistent with citation flows in the patent citation network. Among these IPCs, *H01L-031/00* (Semiconductor devices) has the highest frequency (18 instances), followed by H01G-09/00 (Electrolytic capacitors, rectifiers, detectors, switching devices, light-sensitive or temperature-sensitive devices) (8 instances), H01L-51/00(Solid state devices using organic materials as the active part) (8 instances), and H01M-14/00 (Electrochemical current or voltage generators) (6 instances). Also, companies have a tendency to cite their own patents and cite the same patents in similar patents. For instance, EP901175 and EP1107333 belong to the Fuji Film Corp, and US20030188777, US20030230337, and US20050039790 are owned by Konarka Technologies Inc and their partners, who cite their own patents.

To identify other critical directions of R&D in the field, we conducted an MPA based on key-routes as opposed to the global standard routes outlined above. This approach provides an analysis at different levels of detail, depending on the number of links selected. We explored from the top 10 to the top 50 links looking for a reasonable threshold to identify paths with the greatest weight values in the network. A divergent-convergent pattern became clearest with the top 25 links as the results in Fig. 10 show.

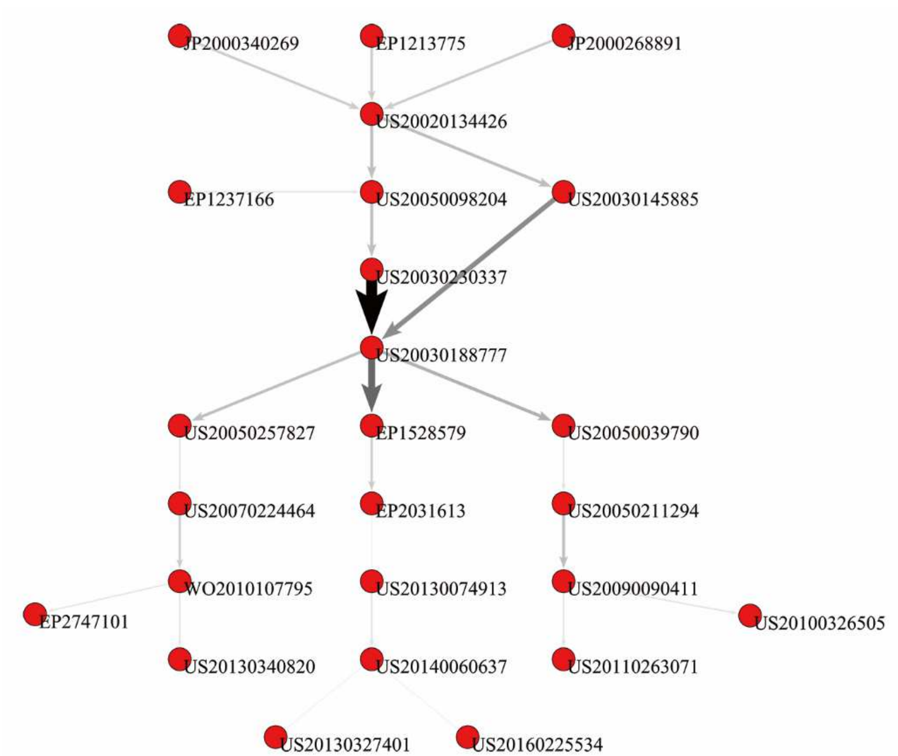


Fig. 10. The main path of DSSCs technology from 1991–2017 using the key-route method

Note: The thickness of the linkage indicates the traversal weights.

To better analyze technology focus and evolution, we extract topic information from "Title+Abstract" field of the patents by using the semiautomatic "term clumping" analysis, and the details of the DSSCs patents along this global key-route are listed in Table 3. Along the main path, most of the DSSCs patents in the early stages primarily discuss the Semiconductor Electrode, including JP2000268891, JP2000340269, EP1237166, US20020134426 and US20030145885. Thereafter, photovoltaic material (e.g. US20050211294 and US20070224464) and photovoltaic facilities and method (e.g. US20050098204 and US20050257827) attract wide attention from DSSCs assignees. A patent for co-sensitizers for dye-sensitized solar cells (US20030188777), held by Konarka Technologies Inc, plays a vital role in this citation network. It protects a photosensitizing agent that consists of a sensitizing dye for receiving electromagnetic energy and a co-sensitizer comprising a coordinating group for co-adsorbing with the sensitizing dye on a surface. The material is suitable for use with flexible photovoltaic cells and enhances the charge transfer efficiency of the sensitizing dye.

Table 3. Details of the DSSCs patents in the main path with the global key-route MPA approach

Publication Number	Application Year	Main Technology Foci	Global Standard
JP2000268891	1999	Transparent Semiconductor Electrode; Multicolored Sensitizing Dye; Transparent Semiconductor Layer	√
JP2000340269	2000	Pigment Sensitized Optoelectric Transducers; Blue Kite Type Titanium Oxide	√
EP1213775	2001	Solid-Type Dye; Photoelectric Conversion Element; Hole Transport Layer; Electrode	√
EP1237166	2002	Photoreceptive Surface; Semiconductor Electrode	
US20020134426	2002	Multilayered Porous Photovoltaic Layer; Porous Semiconductor Layer	√
US20030145885	2003	Semiconductor Electrode, Opposed Electrode, Polymer Electrolyte Gel	
US20030188777	2003	Photosensitizing Agent; Flexible Photovoltaic Cell; Sensitizing Dye	√
US20030230337	2003	Photosensitive Nanomatrix Layer; Charge Carrier Medium; Transmitting Electrode; Mesh Electrode	√
EP1528579	2004	Semiconductor Electrode; Lectrospun Ultra-Fine Fibrous; Titanium Dioxide Layer; Counter-Electrode; Liquid Electrolyte	√
US20050039790	2004	Electrolyte; Gelling Compound; Metal Ions; Organic Compound; Metal Ion	√
US20050098204	2004	Photovoltaic Device; Nano-Structured Template; Transfer-Material	√
US20050211294	2005	Photovoltaic Material; Light-Transmissive Electrical Conductor; Photoconversion	√
US20050257827	2005	Rotation Method; Photovoltaic Facility; Powering Sensor; Photovoltaic Facilities	
US20070224464	2006	Photovoltaic Cell; Cathode, Photoactive Material; Electrical Insulator	
US20090090411	2007	Lower Electrode; Titanium Alloy; Titanium Oxide Electrode; Metal-Oxide Layer	√
EP2031613	2008	Semiconductor Electrode; Dye-Adsorbed Metal-Oxide Nanoparticles; Compress-Sintering Fibers; Metal-Oxide Precursor	√
US20100326505	2009	First Electrode; Photo-Absorption Layer	√
US20110263071	2010	Impregnating Photosensitizing Dye; Preparing Conductive Substrate; Metal-Oxide Layer	√
WO2010107795	2010	Articles; Glass Substrate; Solid State Dye; Photoactive Layer; Metal-Oxide and Dye	
US20130074913	2011	Electrode; Transparent Conductive Substrate; Semiconductor Nanofiber Layer; Semiconductor Superfine Fibers	√
EP2747101	2012	Opto-Electronic Device; Metal Substrate	
US20130340820	2012	Metal Substrate; Clad Material; Nonporous Metal Layer	
US20140060637	2012	Photoelectrode Mounted; Negative and Positive Electrodes; Electrolyte Set; Photoelectrode	√
US20130327401	2013	Composite Dye-Sensitized Solar Cell; Conductive Substrate; Fine Titanium Dioxide Nanoparticles	√
US20160225534	2016	Composite Dye-Sensitized Solar Cell; Scattering Layer, Dye and Electrolyte	√

From this patent onwards, the main path divides into three sub-paths:

1) One continues to focus on improving photovoltaics and photoactive material, such as flexible photovoltaics (e.g., US20050257827) and metal substrates including a cladding material (e.g., US20130340820);
2) A second focuses on counter-electrodes and electrolytes, such as liquid electrolytes (e.g., EP1528579) and nanofiber electrodes (e.g., 20130074913);

3) The third focuses on photoanodes and dyes, such as titanium oxide (e.g., US20090090411) and impregnating photosensitizing dye (e.g., US20110263071).

Overall, these trajectories chart the development of DSSCs from their basic componentry, such as photoelectric conversion elements, to advanced sub-technologies, such as photoanodes, sensitizers, electrolytes, and counter-electrodes, then onwards to composite dye-sensitized solar cells (e.g., US20130327401 and US20160225534).

V. CONCLUSIONS AND DISCUSSION

Tracing the evolutionary pathways of a technology is essential for monitoring the progress of innovation, and MPA is one of the most effective approaches to identifying key technological trajectories within complex patent citation networks. Most studies to date have ignored the essential role patent families play in a citation network and, as a result, the analyses do not completely describe a field's evolution and, thus, have limited practical use. Moreover, technological progress generally occurs over some common and fairly distinct stages, and the citation networks in each stage have their own specific characteristics. Therefore, for an accurate depiction of knowledge diffusion, it is important to analyze patent citations in the context of the technology's stage of development at that time. Hence, in this paper, we presented a framework for identifying both technology evolution pathways and the stages of a technology's development that considers both patent families and patent citations in the context of stage. We introduced technology community evolution and technology specialization indicators to divide the technology's evolution into stages and merged data into patent families to build a more comprehensive citation network. Last, we introduced global standard MPA and global key-routes MPA to identify and trace a set of main technology trajectories.

Based on these analyses, we derive several ideas. First, observing technology changes over different stages can help us to understand and track the mainstream paths of key technologies. Static technical evolution is only well suited for mature technologies or emerging technologies that are in an extended, stable stage of development. Some patents may play a vital role at a certain stage of a technology's development and, as a result, attract a remarkable weighting in some analysis methods. But that does not necessarily mean the patent remains influential throughout the life of the technology. Second, taking patent families into consideration has a remarkably positive effect on constructing the patent citation network and identifying the main patents. The performance of centrality, connectivity, and modularity in the citation network of considering family patents are better than when ignoring them. These network attributes are highly beneficial for discovering critical nodes with MPA. Third, patent citation analysis is a useful method for tracing technological development, and applying MPA to a citation network can distill a complicated citation network down to a small number of highly-influential nodes and links. The identified patents located on the main path may prove to be helpful insights for decision-makers in the field. In general, this method should generate useful technological intelligence regardless of what technology it is applied to, given its purpose is to elucidate technological change processes. For this reason, we believe it can help to identify opportunities for innovation, prospective paths to commercialization, developmental priorities to achieve, and a host of other forward planning goals.

This study also offers some theoretical insights for analysts. Overall, we find that MPA with the multiple key-route approach is an effective tool for tracing technological change. The dynamics of progress are embedded in the very structure of the knowledge diffusion paths – the stories of technological change speak for themselves. Further, technologies invariably emerge, converge, and diffuse in a series of gradual transformations that create a succession of fused, disrupted, and or entirely new guideposts for design. Therefore, patent family information can significantly improve the coverage and practicability of patent citation analysis, and may also indicate the near-term commercial potential and market distribution of a technology.

There are many ways this study could be improved: First, we used an SPLC algorithm to calculate the weight of the vertices in the network. However, these types of algorithms (NPCC, SPNP, and SPC) only work on binary citation networks, and all citation pairs are treated the same way. Current advances in text mining, especially semantic analysis, allow for scaling the relevance of particular citation pairs or publications, which turns a traditional binary citation network into a weighted network that could bring significant advantages. Second, in a complex citation network, the end goal of the MPA method is to simplify the citation network down to only the most significant development paths. But this approach does not consider that the most significant route may not be the route with the largest overall impact. Impact certainly reveals the nodes that have been the most important either at that point in time or because they are positioned at a strategic junction along a trajectory [15]. However, as a metric, impact does not reveal the nodes that will be the change-makers of the future. Indeed, it would be fair to say, that the entire system of citation evaluation does not account for future potential. Third, MPA is seen as a general tool that highlights historical events to illuminate the evolution of technological fields [52]. Therefore, when we interpret MPA results, we not only need to consider the reverse-inheritance effect and the integrator effect, but we also need to ask domain experts to validate these proposed results. All the above points remain open questions deserving of further study.

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