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An assessment of technology forecasting: Revisiting earlier analyses on dye-sensitized solar cells (DSSCs)

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ABSTRACT

The increasingly uncertain dynamics of technological change pose special challenges to traditional technology forecasting tools, which facilitates future-oriented technology analysis (FTA) tools to support the policy processes in the fields of science, technology & innovation (ST&I) and the management of technology (MOT), rather than merely forecasting incremental advances via analyses of continuous trends. Dye-sensitized solar cells are a promising third-generation photovoltaic technology that can add functionality and lower costs to enhance the value proposition of solar power generation in the early years of the 21st century. Through a series of technological forecasting studies analyzing the R&D patterns and trends in Dye-sensitized solar cells technology over the past several years, we have come to realize that validating previous forecasts is useful for improving ST&I policy processes. Yet, rarely do we revisit forecasts or projections to ascertain how well they fared. Moreover, few studies pay much attention to assessing FTA techniques. In this paper, we compare recent technology activities with previous forecasts to reveal the influencing factors that led to differences between past predictions and actual performance. Beyond our main aim of checking accuracy, in this paper we also wish to gain some sense of how valid those studies were and whether they proved useful to others in some ways.

1. Introduction

Newly emerging science and technologies (NESTs) are expected to bring both considerable wealth and numerous opportunities and challenges. As NESTs can be radically novel, relatively fast-growing, and characterized by a certain degree of coherence, these forms of technologies tend to be more dependent on intermittent advances (Rotolo et al., 2017). The anticipated (disruptive) impacts on markets and on society are more difficult to foresee than a steady and incremental innovation process, and the highly uncertain dynamics of NESTs pose special challenges to traditional technology forecasting tools.

In an environment facing the complexity of a growing number of NESTs, decision makers need to capture current and strategic intelligence on a range of technologies and make forward-looking assessments. Over the years, future-oriented technology analysis (FTA) tools have expanded beyond forecasting incremental advances. Two papers made a case for methodological enrichment to address expanding challenges, contributing to the FTA blend of "technology forecasting" and "foresight" approaches (Coates et al., 2001; Technology Futures Analysis Methods Working Group, 2004). Others compile alternative FTA-related methods, distinguishing types and study purposes (Porter, 2010; Rader and Porter, 2008).

Most FTA endeavors now purport to inform policy processes for those addressing Science, Technology & Innovation (ST&I) and the management of technology (MOT). Hence, the ability to explore multiple potential innovation pathways (Robinson and Propp, 2008) becomes essential. Under such a background, the forecasting innovation pathways (FIP) framework including 4 stages and 10 steps has been constructed to analyze NESTs (Robinson et al., 2013). This framework incorporates "tech mining" (Porter and Cunningham, 2005) to ascertain developmental patterns, key participants, and potential application targets by analyzing large datasets drawn from ST&I publication and patent databases, as well as contextual information resources (e.g., ABI Inform). As a multi-step process for analyzing ST&I information resources, tech mining provides empirical knowledge necessary to address, and then help assess mature or emerging fields of science and

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technology (Porter et al., 2011). To complement the tech mining process, expert-based inputs, derived from interactive workshops, help to digest the empirical findings and lay out prospective developmental pathways.

The FIP approach can be treated as a bridge methodology that builds on a strong empirical base by incorporating informal expert opinions. FIP aims to elucidate the forward pathways R&D activities might take in translating ideas into applications and is a valuable tool for exploring future development trajectories (Porter et al., 2015). However, we need to accept that the activity of technology forecasting is focused on changes in technology; it is not deterministic. That is, technology forecasting does not seek to predict a single certain future (Roper et al., 2011a). Therefore, validating past results is an important step in adapting FTA-based methodologies to help analyze complex technologies with significant infrastructure in place.

Photovoltaics is one emerging technology that has gathered much attention over the past several years due to its potential for decreasing costs and its broad applicability. Within this innovative technology, a promising third-generation form of photovoltaics – Dye-sensitized solar cells (DSSCs) – is gathering momentum as an economically and environmentally-viable alternative to traditional devices (Parisi et al., 2014). DSSCs technology has witnessed increasing R&D activity since 1991 and is anticipated to continue toward rapid commercialization in the future (Baxter, 2012). The program in Science, Technology, and Innovation Policy (STIP) at the Georgia Institute of Technology is actively involved in characterizing the nanotechnology industry and its dynamics through data mining techniques, such as bibliographic database analysis (yielding bibliometric data) and patent database analysis (yielding intellectual property data), as well as through text-mining, interviews, and other research methods (Youtie et al., 2018). Additionally, since 2008, the Innovation Co-Lab (STIP, Manchester Institute of Innovation Research, University of Manchester (MIoIR), and the School of Management and Economics, Beijing Institute of Technology) has been analyzing DSSCs R&D activity patterns through a series of studies that include: (1) research profiles and technology opportunity analysis (Guo et al., 2010; Guo et al., 2016; Huang et al., 2011; Ma et al., 2014; Wang et al., 2015); (2) collaboration networks and patterns (Wang et al., 2014a, 2014b); and (3) the FIP approach, which includes technology delivery systems (Guo et al., 2012a), estimating innovation risks (Guo et al., 2012b), and technology roadmapping of evolutionary pathways (Huang et al., 2014; Zhang et al., 2014a, 2014b, 2016; Zhou et al., 2014).

With such objectives in mind, we revisit our earlier assessments and projections with an updated DSSCs data collection to assess the accuracy of past forecasts and rethink how to improve the reliability of technology forecasting. FTA purports to inform MOT and ST&I policy processes. Yet, rarely do we revisit forecasts or projections to ascertain how well they fared, nor does previous research pay much attention to assessing the efficacy of the forecasting method used. One of our aims is to check accuracy, to gain some sense of how valid those studies were and whether they proved useful to others in some ways. Additionally, we want to assess the degree to which these analyses did or did not make good use of the information available at the time. Moreover, we seek indications of which information is key, and how FTA processes can better use that information.

The remainder of this paper consists of five sections. Following this general introduction, the related reviews on technology forecasting are provided in the "Related Literature" section. The "Framework and Data" section describes the framework we used for assessing the technology forecasts along with the data we used in the analysis. The "Results and Findings" section explores how the stage of a technology's development was identified, the focal countries and regions, the prominent technological actors, the distribution of sub-fields, and the past and future potential of various sub-technologies through a comparative analysis. The focus is on comparing recent technology activities with previous forecasts to seek the influencing factors that led to differences between past predictions and actual performance. The "Conclusions and Discussions" section reviews the results in terms of the proposed research questions and identifies the limitations and promising opportunities found in this research for the future.

2. Related literature

Technology forecasting offers means to help enterprises formulate technology strategies and policies by identifying core and emerging technologies (Cho and Shih, 2011). Much research has been undertaken in the study of technology forecasting, and this section provides a review of relevant technology forecasting methods in the literature.

2.1. Qualitative methods: represented by Delphi technology forecasting approach

The Delphi method is viewed as an efficient procedure for obtaining a reliable consensus opinion from a group of experts through a series of intensive questionnaires interspersed with controlled opinion feedback (Dalkey and Helmer, 1963). It is a qualitative decision-making method and the accuracy of the decisions are mainly determined by the knowledge level of the experts. Delphi is well suited to technology forecasting, particularly because of its ability to produce long-range and large-scale forecasts, and, with this method, core technologies can be identified and forecasted relatively easily (Cho et al., 2004).

However, conventional Delphi methodologies have some drawbacks and, therefore, several alternatives have been developed to overcome these shortcomings. For example, Yun et al. (1991) developed a technology forecasting approach based on a semi-Markov model, which primarily focuses on capturing the information that has been skipped in conventional Delphi survey data. To enhance Delphi's analytical power, Hussler et al. (2011) proposed increasing diversity within the panel groups. Bloem da Silveira Junior et al. (2018) combined other techniques, including morphological analysis, decision matrices, interviews, and prioritization analysis, with the Delphi method to construct technology roadmaps. More recently, a real-time spatial Delphi technique was introduced to provide an innovative way of eliciting expert opinions using a simple and intuitive platform (Di Zio et al., 2017). Wakefield and Watson's (2014) reappraisal of Delphi 2.0 perhaps provides one of the best showcases for how a qualitative approach such as Delphi can be quite useful for exploring complex issues in a given domain by gathering selected experts on a particular topic.

2.2. Quantitative methods: represented by Science & Technology(S&T) data analysis

Methods based on expert opinions, such as Delphi, provide a subjective consideration of contextual changes through the implicit mental models that each expert has internalized about the nature and likelihood of change. However, these methods tend to be both time-consuming and costly. To ameliorate these problems, many researchers in the field of technology forecasting have turned to quantitative methods. A combination of tools can be used to help properly forecast technology trends (Daim et al., 2006). Quantitative methods are useful when there is enough directly measurable data available (Rueda and Kocaoglu, 2008). Science & technology documents, such as patents and scholarly papers, can provide such data to a certain degree (Harell and Daim, 2009).

Many interdisciplinary quantitative research methods have integrated bibliometric and patent analysis into technology forecasting. Overall, these approaches can be divided into four types. (1) Multi-indicator-based analyses, which introduce new metrics, like citations per patent, information about patent families, patent share, increases in the number of patents, and patent activity. For example, Choi et al. (2014) analyzed next-generation mobile communication. (2) Text-based analysis including machine learning approaches, such as clustering similar technologies based on the patent feature vector (PFV) (Kyebambe et al. (2017), K-means clustering based on support vector clustering (KM-SVC) (Jun et al., 2012), and Latent Dirichlet Allocation (LDA) for topic identification (Kim et al., 2015). (3) Citation-based analyses include You et al.'s (2017) forecast on the development trends of coherent light generator technology. (4) Hybrid approaches, such as enhancing the future-oriented performance of morphology analysis by combining it with conjoint analysis and citation analysis (Yoon and Park, 2007), applying co-classification analysis, co-word analysis and main pathway analysis to reveal implicit or unknown patterns and discover significant clues about technology prospects (Huang et al., 2017).

2.3. The combination of qualitative and quantitative analysis

However, exclusively using either a qualitative or a quantitative approach may result in an incomplete view of a technology development process (Haegeman et al., 2013). Technology forecasting is sometimes viewed as an effort to collect information to posit about the future, the plausibility and limits of a technology, its internal consistency and conformity with models and data, or its consistency with expert judgment (Eerola and Miles, 2011). Expert knowledge might give a reasonable explanation of qualitative data, but combining expert knowledge with a qualitative appraisal can often improve forecast accuracy (Chen and Kung, 1984). As some researchers point out, a quantitative approach, such as text mining, can reveal invisible information in patent data, and citation analysis may provide insights into the evolutionary pathways of a technology. But also, expert analysis can provide intelligence not readily discerned from data analyses, or that a layperson cannot glean (Li et al., 2015).

This type of research has been conducted in several technology fields. For example, Chen et al. (2010) combined bibliometric & patent analysis with an expert survey to forecast the hydrogen energy and fuel cell technology. Zhang et al. (2013) generated a global technology roadmap for electric vehicles using a hybrid bibliometric and qualitative methodology.

While much of the research above includes aspects of the design of technology forecasting approaches, some studies focus on the selection and comparisons of technology forecasting methods. Selecting a forecasting technique that considers the characteristics of the technology and the resources needed, such as cost and time, is essential. Intepe et al. (2013) proposed a solution for selecting a technological forecasting technique that includes seven selection criteria and twelve forecasting alternatives. Cheng et al. (2008) adopted a fuzzy AHP method to obtain selections for technology forecasting methods by professionals. Wilmot (1971) published a brief critical analysis of how various existing technological forecasting methods might influence the resulting conclusions about the nature of future developments.

This limited reviews shows many attempts to analyze future-oriented activities or provide insights to assist technology forecasting. However, research that revisits existing technology forecasts or its methods seems relatively rare. By re-examining the analyses and conclusions produced with technology forecasting methods, adjustments and suggestions can be made to enhance their accuracy and reliability. To this end, this paper is an attempt to assess technology forecasting, especially science & technology data-based forecasting, through an empirical comparison of our past technological forecasts on DSSCs and current, updated analyses based on actual information that includes a further six years of evolution.

3. Framework and data

3.1. Conceptual framework

Technology forecasting focuses on changes in technology, such as its functional capacity, timing, or significance. Within the scope of technology forecasting, it is common to answer variants of the so-called reporter's questions:

(1) “What?”–what technologies or parts of technologies are likely to become the most promising sectors?
(2) “When?”–when will those technological trends reach certain levels?
(3) “Who?”–who will play a leading role in the R&D and potential market for a given technology?
(4) “Where?” –which countries or regions will make outstanding contributions to a technology's performance?
(5) “How?”–how will a technology evolve from one stage to the next?
(6) “Why?” – why will a technology evolve, and why will that change happen during a certain period of time?

Compared to technology forecasting itself, assessing a technological forecast or the method used to produce the forecast seeks to evaluate the activity in technological development from the perspective of data collection, technology life cycle analysis, basic technology profiling, and enhanced technology detection. The time-lag between past and present provides a window for revisiting previous forecasts and analyses. An overview of the framework we used for assessing data-driven technology forecasting is shown in Fig. 1.

Technology forecasting is likely to be more successful when diverse and effective sources of information are integrated to produce a convincing and holistic portrait of possible futures. As data sources and data quality become the foundational factors in most data-based technology forecasting systems, so it is necessary to reconsider whether the search strategy is effective or acceptable in the new circumstance. Through experience, we have come to realize that searching for data in a domain with many commonly used terms can be particularly challenging. Hence, it is often easier to identify relevant research on a technical topic like DSSCs, than one involving a lot of broader computer science or managerial terminology, e.g., “Big Data” (Huang et al., 2015). Selecting the right data source depends upon the specific technologies and topics being addressed. Further, the research question often drives the search for a corresponding data source. However, overall multiple sources of data are often beneficial for gathering a greater amount of information and for making more accurate forecasts. Patent data usually comprises a main source of information because it not only provides actual clues about the most important discoveries companies and inventors seek to protect, it also provides information about technologies that are nearing the market.

Technology forecasting methods can be classified as either extrapolative or normative – namely, by whether they extend present trends or look backward from a desired future objective to track the developments needed to achieve those goals (Roper et al., 2011a). Given that the main purpose of this assessment is to revisit previous analyses, we try to compare results using the same or a similar approach as the original study. However, one visible discrepancy that needs to be accounted for is that technology forecasting based on real activity must pay attention to both the functional capacity and relevant characteristics of the technology, and also consider the structural interactions between the technology and the elements of its context. Technology often presents different development tracks; therefore, it is necessary to consider the technology life cycle when creating a distinct R&D strategy plan. The technology life cycle comprises a pattern of dynamic characteristics pertaining to technology, in which its innovative and economic outcomes change over time. Therefore, after obtaining the dataset of a target technology, it is important to judge which stage the technology reaches at given times. In general, the life cycle can be divided into four parts: seeding phase, growth phase, maturity phase and decline phase. When we assess the technology stage, the main object is to analyze whether the cycle is maintaining or has shifted to the next developmental phase.

Similar to technology forecasting, the analytical scope of assessing technology forecasts centers on the key questions of “who, what, where,

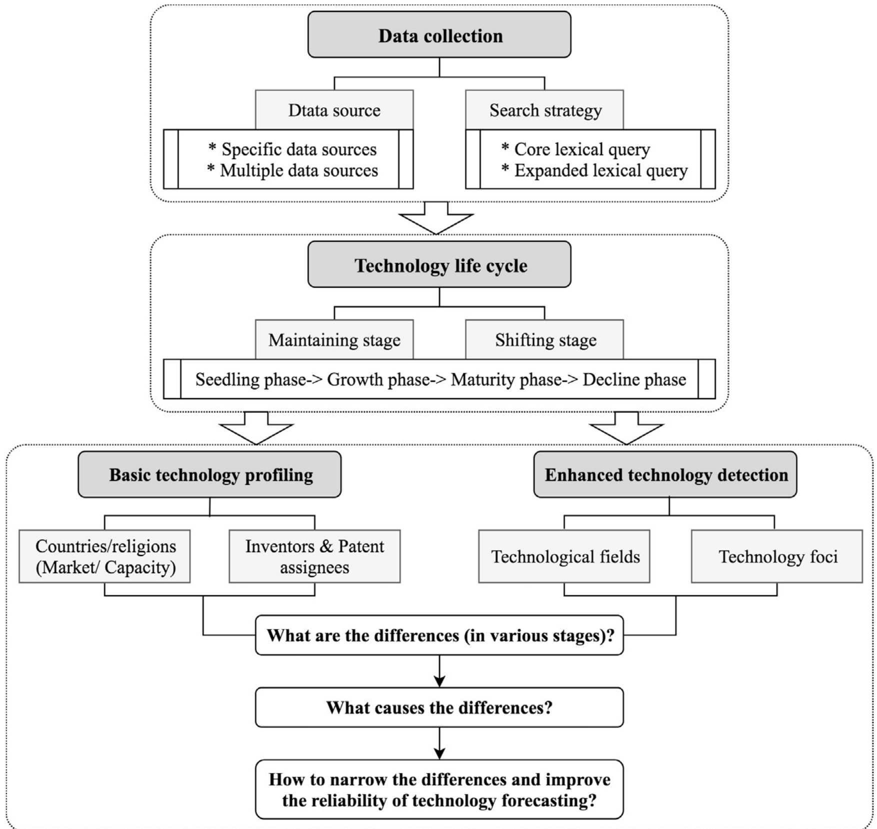


Fig. 1. A framework for assessing data-driven technology forecasting.

when, how, and why." In technology forecasting, one often wants to identify the leading country, the main R&D institutions, and the most prominent inventors, based on the assumption that they will perform about as well going forward as they have in the past. However, the process of technological evolution is dynamic, so the role of a technological actor may change through various stages of development. Likewise, the best conceptual framework for representing an organization's beliefs, assumptions, and goals may also change. For such a basic profiling respective, the main research questions addressed here are 1) what role shifts do we see for countries (priority country and family country) and regions, and 2) how do inventors and patent assignees shift among leading, emerging and declining status in various stages? Further, a key purpose of much technology forecasting is to oversee the larger technological picture under the conditions at the time, so what technological fields transform and how technological foci evolve, turn out to be essential issues. Further exploration on technological fields and technological foci are treated as enhanced technology detection. Along with basic technology profiling, the primary task of these "revisits" is to answer the following three questions:

- First, **what are the differences between past predictions and actual performance**? These differences can be revealed by applying the same or a similar approach as the past forecast to analyze the current situation. Examining past performance to improve present performance can also be used to strengthen future approaches to technology forecasting. Therefore, examining the results of past forecasts can be beneficial for determining whether they were successful in limiting uncertainty (Roper et al., 2011b). Comparative processes that involve either single or hybrid methods can be used to conduct the analyses from multiple dimensions.
- Second, **what causes differences between earlier forecasts and actual developments?** This question seeks to identify factors that have influenced the results throughout the forecast phases. It is necessary to distinguish whether these factors are internal (such as data limitation) or external (such as misleading methods), contextual oversights (e.g. the growth of disruptive technology) or faulty assumptions (e.g. unconscious biases).
- Third, **how to narrow the differences and improve the validity and reliability of technology forecasting**? The narrow range of probable futures presented in a forecast, augmented with continued updates, provides a sound basis for moving forward to implementation. Therefore, assessing a technology forecast means tracking the differences, explaining the uncertainties, and bridging the gap by improving the technological parameters, surveying the environmental context, and converging diverse approaches based on complementary strengths.

This paper attempts to identify the strengths and weaknesses of our previous DSSCs analyses in terms of data characteristics, projection accuracy, and the stability of the actors. The results should provide insights for improving current FTA methodologies and validating other FTA analyses. For this analysis, we mainly selected 2010 as the boundary for comparison between our previous studies and this study.

3.2. Data retrieval

Obviously, in a data-driven analysis, the quality of the data is critical. Accurate data-based forecasting of emerging technologies is still problematic due to data issues, as affected by the qualities of data sources and the strategy of data retrieval. In the past few years, our team has worked with multiple DSSCs search strategies. The search strategy for DSSCs has been tuned several times. A prominent previous search strategy and the current one are arrayed in Table 1. After repeated verification, the search query we favor is: ABD = ((Dye* or Pigment*) and (Sensiti*) and (Solar* or Photovoltaic*) and (Cell* or Batter*)).

Table 1
Past and current DSSCs search strategies.

Type	Search strategy
Past	ABD = (((dye-sensiti*) or (dye* same sensiti*) or (pigment-sensiti*) or (pigment same sensiti*) or (dye* adj sense)) same ((solar or photovoltaic or photoelectr* or (photo-electr*)) same (cell or cells or batter* or pool*))) OR ((ABD = (((dye- ADJ photosensiti*) or (dye same photosensiti*) or (pigment- ADJ photosensiti*) or (pigment same photosensiti*)) same ((solar or photovoltaic or photoelectr* or (photo-electr*)) same (cell or cells or batter* or pool*))) OR ABD = (((dye- ADJ optoelectri*) or (dye same optoelectri*) or (pigment- ADJ optoelectri*) or (pigment same optoelectri*) or (dye- ADJ opto-electri*) or (dye same opto-electri*) or (pigment- ADJ opto-electri*) or (pigment same opto-electri*)) same ((solar or photovoltaic or photoelectr* or (photo-electr*)) same (cell or cells or batter* or pool*))))) AND (ICR = (H01G* or H01M* or H01L* or G03C*)) OR ABD = ((((dye or pigment) and sensiti* and (conduct* or semiconduct*)) same electrode*) and electrolyte*) AND (PY > = (1991) AND PY < = (2016));
Current	ABD = ((Dye* or Pigment*) and (Sensiti*) and (Solar* or Photovoltaic*) and (Cell* or Batter*)) (PY > = (1991) AND PY < =(2016))

Note: ABD denotes Abstract; ICR represents the International Patent Classification (IPC); PY denotes the publication year.

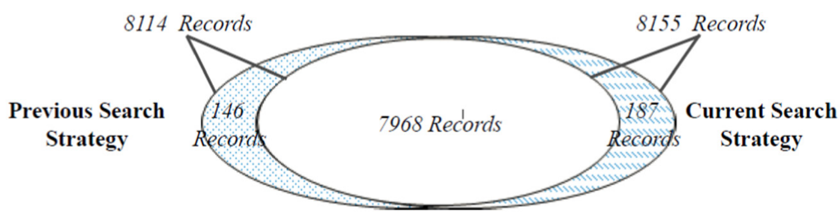


Fig. 2. The comparative search results in literature and patents.

In this paper, we update DSSCs searches in Derwent World Patents Index (DWPI) from Derwent Innovation (DI), a platform that provides a comprehensive patent solution covering more than 50 patent-issuing authorities. The comparative search results are shown in Fig. 2. We can see that current retrieval results cover most of the previous records and don't present a large difference compared with the previous search results. The dominant feature of Fig. 2 is that ~98% of the patents retrieved are common to both searches.

We read the abstracts of the 333 records (187 + 146) not included in both search sets. We conclude that the newly added 187 records mostly belong in the scope of DSSCs [to illustrate – "manufacturing method of dye sensitive solar panel for display substrate of cellular phone, involves coating nano-sized crystalline titania powder on glass substrate, and plasticizing titanium film at specific temperature" (Patent NO. KR2013050322)]. And, the excluded 146 records fall mostly outside the category of DSSCs [e.g., "electrochromic device, useful e.g. as rearview mirror, comprises first substrate having transparent conductor coated surface, second substrate having second conductor coated surface, and electrochromic medium disposed between substrates" (Patent NO. US2004257633)]. Above all, the current search terms are much easier to understand. Therefore, we believe our current search terms are effective to conduct this research. Ultimately, we retrieved the records from DWPI database on September 10. 2017, resulting in 8155 DSSCs-related patent records published between 1991 and 2016.

4. Results and findings

4.1. Refine technology life cycle

Understanding long-term patterns of innovation is the most fundamental aspect of technology forecasting and public policy planning. Technology forecasting calls for a dynamic perspective, so identifying the current stage in a technology's life cycle is essential for estimating its future development trends (Gao et al., 2013). Various growth curves have been used to represent technology's life cycles, such as logistic, gompertz, weibull curves and the generalized function (aka richards' curve). Overall, the analytical results from past literature demonstrate that models based on logistic growth curves (S-curves) are a highly effective means of quantifying technology forecasting with cumulative publications or patents activity (Chen et al., 2011).

Logistic analysis involves the decomposition of growth and diffusion patterns into S-shaped logistic components. Most previous studies tend to apply a logistic model without further consideration. However, the technological development trends can sometimes resemble a succession of several curves (i.e., so-called envelope curves), and the overall logistic behavior of a technology tends to be hard to discern and analyze if the selection of growth form is inappropriate. Here, we introduce the online analytics tool- Loglet Lab (http://www.logletlab.com) to assist our analyses. The parameter statistics for the period 1991–2010 and 1991–2016 are shown in Table 2. In both stages, the results for most parameters indicate that a 1-wave model performed better than a 2-

Table 2
Parameter of a logistic model for DSSCs patenting, 1991–2010 and 1991–2016.

	1991–2010				1991–2016			
Parameter	1-Wave	2-Wave			1-Wave	2-Wave		
		Phase 1	Phase 2	Whole fit		Phase 1	Phase 2	Whole fit
SSE	26,489	597,313	100,600	597,313	123,916	2,606,835	401,407	2,697,728
RMS	47	173	120	173	85.4	361	200	322
MAD	43.7	131	98.8	131	70	278	171	234
MAPE	0.115	0.535	0.836	0.518	0.0637	0.473	0.646	0.443
SE	54.3	187	159	207	94.1	392	239	367
ln[MLE]	−63.2	−132	−43.4	−132	−99.7	−148	−67.2	−188
AICc	135	272	101	283	207	304	144	393
R^2	0.994	0.952	0.967		0.997	0.962	0.996	

Note: SSE - sum of square errors; RMS - root mean square; MAD - mean absolute deviation; MAPE - mean absolute percent error; SE - standard error; MLE - maximum likelihood estimation; AICc - Akaike information criterion for model selection.

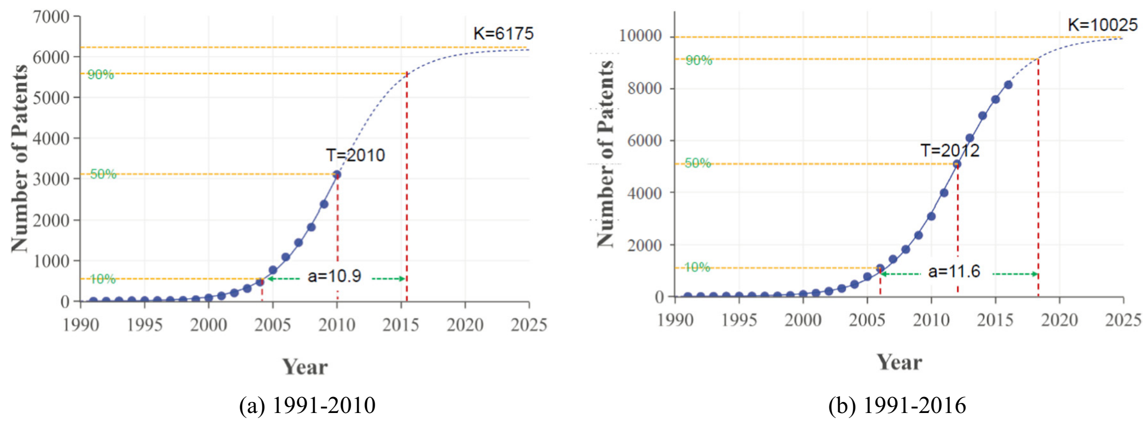


Fig. 3. Composite fit of the DSSCs patents for 1991–2010 and 1991–2016.
Note: 'K' means the "carrying capacity" of the model (the saturation value of the S-shaped logistic); 'a' is the "growth rate", which is related to the time for the logistic curve to rise from 10% of k to 90% of 'k'; 'T' is the midpoint of the logistic curve (the time when p(t) reaches 50% of 'k'.

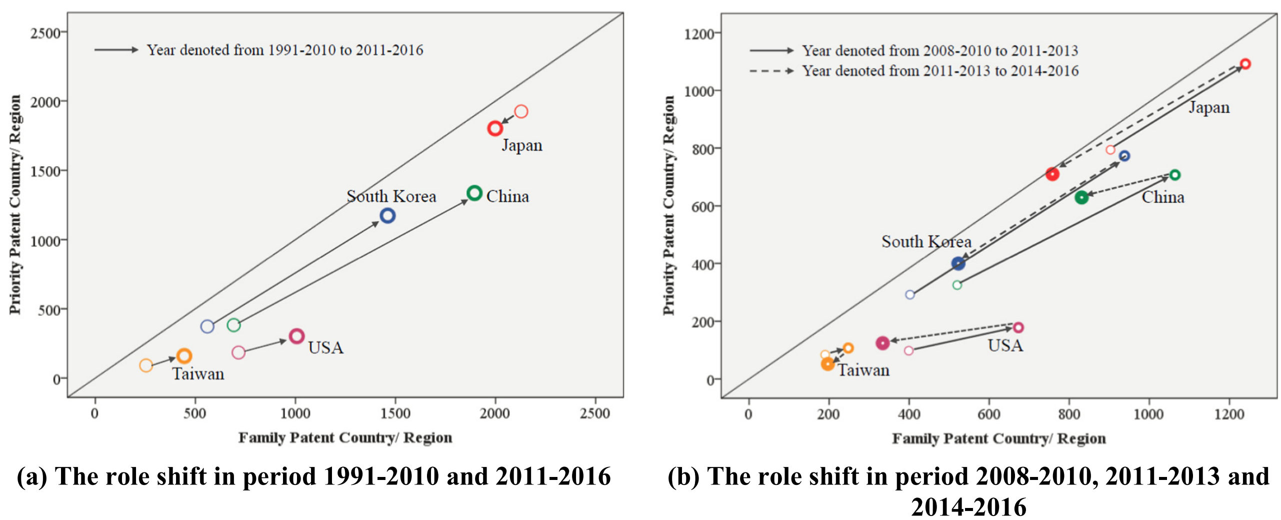


Fig. 4. Leading countries/regions in DSSCs in different periods.

wave model. Thus, we chose the 1-wave logistic model.

Fig. 3 plots the composite fit by showing trends based on cumulative activity. The patents drawn from the DWPI database exhibited a remarkable increase after 2000. Both fits predict sustained growth after 2010, but the fit for 1991–2016 predicts a descending trend after 2012. Even though the time lag is a common factor that cannot be ignored, the trend for cumulative patents represents an inflection point for slower growth.

To further judge the DSSCs' technology life cycle, we also model the growth using S-shaped curves. The parameterization of the logistic function, which is useful for time-series datasets, is also added to Fig. 3. What is surprising is that the midpoints for the two logistic curves and the carrying capacities are different. In general, a technology's life cycle can always be divided into four stages: the seeding stage, the growth stage, the maturity stage, and the saturation stage. The midpoint is treated as the sign where a technology enters the maturation stage. Based on this assumption, we can identify that DSSCs are currently entering the maturation stage, where management decisions tend to be about evolutionary improvements in features, quality, and costs. Moreover, DSSCs are likely to enter the saturation stage around 2018, when other new and emerging solar cell technologies might be garnering more attention. Such a conclusion could not be drawn based on the data up to 2010. Further, if the technology forecast was made in 2010, the results would probably show that DSSCs technology would reach maturity in 2010, rather than 2012. However, it is important to note that this problematic judgment is more likely due to inadequate data rather than the forecasting method itself. Therefore, with frequent forecasts, it is necessary to limit the time horizon to an appropriate range.

4.2. Compare basic technology profiling

4.2.1. The changes in technical powers and technological markets

At the country level, the priority country and the patent family country are the main dimensions of technology forecasting activities. The first priority country generally serves as a proxy for the geographical origin of the patents (since most patents don't provide inventor location). Considering the high cost of patent applications and maintenance, patents pursued in multiple countries tend to have a higher perceived commercial potential. In general, more patent applications in a certain country or region reflect a higher perception of a commercial market for developing this technology. So, patent family analysis is used to understand the layout of a country's potential markets.

To better figure out any gap between what we indicated before and the current situation, we select the leading 5 priority/family countries/regions and plot the related value in different stages. The arrows show the value changed from certain stages to next stages, shown as Fig. 4.

The work conducted by Zhou et al. (2014) and published in 2014 by using the data from 1991 to 2012 (the data are incomplete for 2011 and 2012, while the data in 2010 are almost complete) figured out the following points: 1) the leading countries/regions were different for each period; 2) the DSSCs patenting concentration spread from Europe to Japan, to the US, and then on to the whole world; 3) Japan and the US were major countries with a lot of DSSCs patents; South Korea also had heavily engaged DSSCs in recent years.

In Fig. 4(a) and (b), the x- axis represents patent family country/regions and the y- axis represents priority country/regions. Both from the perspective of priority country/regions and patent family country/regions, the findings partly accord with previous conclusions that Japan gains the advantage in the past period, and South Korea plays a more and more important role in recent years. Japan holds an absolute technical advantage in the DSSCs field with outstanding performance in the application of inventions throughout the period and has held the greatest potential market share for the past 20 years. South Korea has also been very active in the field since 2008, holding a favorable position until the most recent period. But the emerging role of China was missed by our previous analyses. This may be due to rapid growth being hard to predict in the early stage with limited information. In fact, China has played a notable role after 2011 when China's share of patent applications increases significantly. In addition, the number of patents that obtain priority in the US keep relatively stable, in every stage.

Compared with taking the whole stage as a time window, the trend in the recent 3 years can better profile the situation looking forward, both in 1991–2010 and 2011–2016, see Fig. 4(b). Looking at the observations for 2008, we can sense that both China and South Korea have the potential for growth into a promising product market. And, in fact, this prediction is verified by the data for 2011–2016. Based on the trends for 2014–2016, China is likely to attain the greatest proportion of market share in the near future, and China, Japan, and South Korea will continue to be the key players in the technological field of DSSCs. On one hand, patenting concentration is spreading from regions to the whole world; on the other hand, Asia is becoming the most desired patenting target, which goes beyond expectations of our previous research.

For the kind of omissions and discrepancies in market expansion and application activity, the role shift patterns are mainly affected by national policy, because government plays a more and more important role in introducing and promoting the development of emerging industries. The government's supports stimulate vigorous development, but when the external environment and internal policy change, the industry in question is apt to slump.

4.2.2. The alternation of highlighted technological actors

We now turn to the most prominent organizations in technological exploration and patent applications. In our previous two papers published in 2012 (Guo et al., 2012a; Guo et al., 2012c), the main patent assignees are indicated. But as the time period used in these papers is inconsistent, so the leading actors and their roles are different. The comparative results of leading patent assignees in DSSCs fields can be seen in Table 3.

Internal actor analyses for informing a technology delivery system model for DSSCs conducted by Guo et al. (2012a) indicated Samsung SDI Co. Ltd., Konarka Technologies Inc., Fuji Film Corp., Nanosolar Inc., Nanosys Inc. and Sony Corp. stand in the leading positions. But one year later, the situation changed, as viewed from the other research (Guo et al., 2012c). Except for Samsung SDI Co. Ltd., Konarka Technologies Inc. and Sony Corp., who still stand in leading positions, Nanosolar Inc. and Nanosys Inc. are replaced by Fujikura Ltd., Sharp Kk. and Dong Jin Semichem Co. Ltd. After tracing the message offered by official introduction and commercial reports, we find some clues related to their backgrounds and development history. Nanosolar Inc., a developer of solar power technology, used thin film technology to manufacture CIGS solar cells since 2002, but ultimately failed commercially in 2013. Nanosys Inc. maintained its role in designing products for displays based on quantum dots by developing one of the largest quantum dot patent portfolios with over 200 issued and pending patents worldwide.[1] The use of inorganic semiconductors as effective light sensitizers in a DSSCs configuration has awakened great interest in the past few years, in opposition to the conventional DSSCs, inorganic quantum dots play a direct role in the recombination process (Hod et al., 2011). For Nanosys, quantum dot enhancement film become its development foci, and that might be the most important clue of the role change.

When we looked for the leading technological actors in the current stage, Fujikura Ltd., Fuji Film Corp., Sony Corp., Samsung SDI Co. Ltd., Sharp Kk. and Dong Jin Semichem Co. Ltd. still keep their competitive advantage in the technology battles and commercial competition. Konarka Technologies Inc. and Nippon Oil Corp. no longer stand out in this recent stage. Konarka Technologies Inc., was a solar energy company founded in 2001; it obtained the licensee rights to DSSCs technology from the Swiss Federal Institute of Technology (EPFL), a pioneer in DSSCs research. However, this promising company filed for Chapter 7 bankruptcy protection and laid off its approximately 80-member staff in late May 2012.[2] For the Nippon Oil & Energy Corporation, a Japanese petroleum company, its main businesses include crude oil, petroleum products and other energy-related activities. In 2008, Japan's Sanyo Electric Co. Ltd. has agreed to start talks with Nippon Oil Corp. over a thin-film solar cell joint venture, and to launch a joint company named Sanyo ENEOS Solar Co. Ltd. for the production and sale of thin-film solar panels in 2009. However, Sanyo ENEOS Solar has not brought great success for Nippon Oil Corp, and the role of Nippon Oil Corp. is replaced by other newcomers in DSSCs.

In addition, we not only highlight the leading patent assignees across the whole period of study, but also on the emerging actors in relatively recent years. The active technology assignees in 1991–2010 and 2011–2016 are plotted in Fig. 5. These 13 assignees were selected according to their top-5 ranked performance in the 1991–2010, 2008–2010, 2011–2016, and 2014–2016 periods. The lines in the scatter plots indicate the median values of the assignees. The detailed patent activity information is provided in Table 4.

From our observations of the scatterplots and Table 4, we classified these assignees into three types:

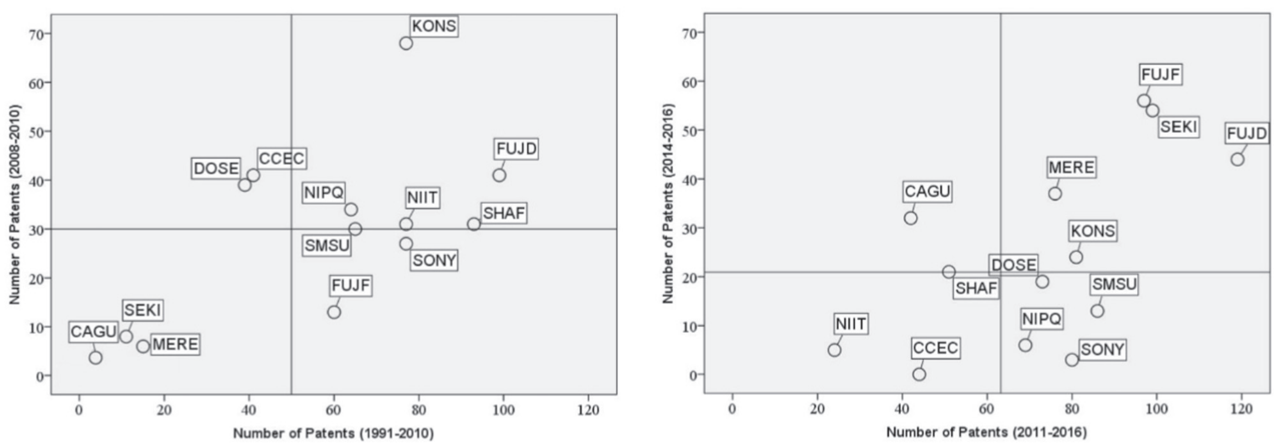
- Leading actors, who are active in every interval, including recent years. Fuji Film Corp. (FUJF) is the leading patentee in every period, indicating its strong and persistent ability for technological innovation. Other leading patent assignees, such as Konica Corp. (KONS) and Fuji Film Corp. (FUJF) also performed well in patent activity in the past two decades.
- Declining actors, who performed well in the initial stage but have become relatively inactive in the recent stage. Some have not even applied for patents. Sony Corp. (SONY) was rather active in the early stage, but has gradually lost their advantage, especially over the past three years. The same is true for some other assignees, including Samsung SDI Co. Ltd. (SMSU), Dainippon Printing Co. Ltd. (NIPQ), Dong Jin Semichem Co. Ltd. (DOSE), Dokuritsu Gyosei Hojin Sangyo Gijutsu So. (NIIT), and Irico Group Co. Ltd. (CCEC).
- Emerging actors, who were in the shade at the beginning of development but have performed noticeably better in recent stages. These actors may not have played a core role in establishing the technological market, but they have the potential to impact their particular area in the near future. These assignees include Sekisui Chem. Ind. Co. Ltd. (SEKI), followed by Merck Patent Gmbh. (MERE) and Shanghai Inst. Ceramics Chinese Acad. Sci. (CAGU).

[1] http://www.nanosysinc.com/who-we-are/

[2] https://www.bostonglobe.com/business/2012/07/07/why-did-solar-cell-company-konarka-fail/tDEdGzmMQO6nNF55RfjvNJ/story.html

Table 3
Comparative results of leading patent assignees in DSSCs fields.

Source	Guo et al. (2012a)	Guo et al. (2012c)	Current research
Time span	1991–2009	1991–2010	1991–2016
Patent databases	DWPI	DWPI	DWPI
Leading assignees	Samsung SDI Co. Ltd. (16)	Samsung SDI Co. Ltd. (65)	Fujikura Ltd. (218)
	Konarka Technologies Inc. (8)	Nippon Oil Corp. (27)	Konica Corp. (158)
	Sony Corp. (6)	Fujikura Ltd. (17)	Fuji Film Corp. (157)
	Fuji Film Corp. (6)	Sony Corp. (17)	Sony Corp. (157)
	Nanosolar Inc. (6)	Sharp Kk. (17)	Samsung SDI Co. Ltd. (151)
	Nanosys Inc. (6)	Dong Jin Semichem Co. Ltd. (16)	Sharp Kk. (144)
		Konarka Technologies Inc. (11)	Dainippon Printing Co. Ltd. (133)
			Dong Jin Semichem Co. Ltd. (112)



(a) The active technology assignees in 1991-2010 (b) The active technology assignees in 2011-2016

Fig. 5. Scatterplots of the active technology assignees for (a) 1991–2010, and (b) 2011–2016.

Table 4
Top patent assignees in different periods, 1991–2016.

Patents assignees	Records	1991–2010	2008–2010	2011–2016	2014–2016	Role
Fujikura Ltd. (FUJD)	218	99	41	119	44	Leading
Konica Corp. (KONS)	158	77	68	81	24	Leading
Fuji Film Corp. (FUJF)	157	60	13	97	56	Leading
Sony Corp. (SONY)	157	77	27	80	3	Declining
Samsung SDI Co. Ltd. (SMSU)	151	65	30	86	13	Declining
Sharp Kk. (SHAF)	144	93	31	51	21	Leading
Dainippon Printing Co. Ltd. (NIPQ)	133	64	34	69	6	Declining
Dong Jin Semichem Co. Ltd. (DOSE)	112	39	39	73	19	Declining
Sekisui Chem. Ind. Co. Ltd. (SEKI)	110	11	8	99	54	Emerging
Dokuritsu Gyosei Hojin Sangyo Gijutsu So. (NIIT)	101	77	31	24	5	Declining
Merck Patent Gmbh. (MERE)	91	15	6	76	37	Emerging
Irico Group Co. Ltd. (CCEC)	85	41	41	44	0	Declining
Shanghai Inst. Ceramics Chinese Acad. Sci. (CAGU)	46	4	4	42	32	Emerging

Looking back over the discrepant role changes of leading DSSCs patent assignees, we see the notable role in previous R&D has changed a lot: Samsung SDI Co. Ltd. and Sony Corp. presented a declining trend in recent years; Konarka Technologies Inc. and Nanosolar Inc. came upon bankruptcy when facing various troubles in terms of technological bottlenecks, slow development cycle, complex production problems and external competitors; Nanosys Inc. turned its efforts to quantum dot sensitized solar cells rather than DSSCs. The super-companies, such as Samsung SDI Co. Ltd., Sony Corp. and Fuji Film Corp., have enough capacity to develop and update technologies, and it is relatively easy for them to obtain competitive advantage. But for the domain's emerging actors, such as Konarka Technologies Inc. and Nanosolar Inc., their developments heavily depend on funding from venture capital firms. Therefore, when we monitor such players, we cannot fully focus solely on empirical patent information, but also need to consider the company background to further check and enrich this 'competitive technical intelligence' through human expertise.

4.3. Validate enhanced technology detection

4.3.1. The transformation in distributed technology fields

Another essential aspect of technology forecasting is understanding a technical domain at the right level of aggregation. The systematic properties of a patent classification system, such as International Patent Classification (IPC), are used to identify the specific detailed technological areas that make up different technologies and industries.

Previous work by Zhou et al. published in 2014 (Zhou et al., 2014) used 8-digit IPCs to trace the evolutionary path for DSSCs by dividing patent records into several time intervals, and identified key subordinate research areas for different time intervals. Based on the

Table 5
Main analyses and predictions of sub-technology fields using 8-digit IPCs.

IPC	Main technology content	Analyses and predictions
H01L-31/04	Semiconductor devices adapted as photovoltaic [PV] conversion devices.	It is a core research area within the DSSCs industry and has maintained a rapid growth rate. There is a high possibility that it will stay in the leading position in this industry for several years to come.
H01M-14/00	Electrochemical current or voltage generators (in energy conversion processes).	Same with H01L-31/04.
H01G-09/20	Light-sensitive devices.	It changes steadily and advances to a different level with each stage. The research attention has increased at a relatively constant rate.
H01L-31/042	PV modules or arrays of single PV cells.	It has become a popular research area.
H01L-51/42	The technology that employs organic materials as the active part for solid state devices.	It is an emerging sub-technology that is rapidly developing.
C09B-23/00	Methine or polymethine dyes, e.g. cyanine dyes.	It increases slowly but steadily. Nevertheless, this is an important area for DSSCs, so more attention should be paid to this subfield.
H01M-10/40	Organic electrolyte (transferred to H01M 10/05-H01M 10/0587).	It emerges during the period of 2000–2003, but this technology nearly disappears after 2008.

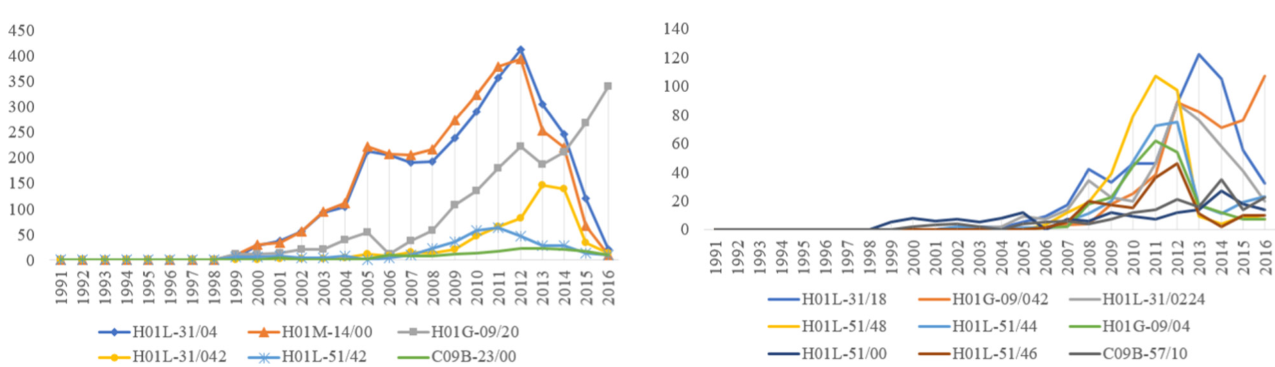
Note: Based on the paper indicated, the data for the time period from 1991 to 2009 are accurate, but for the years 2010 and 2011, data values are estimated. The original evolutionary trend map for DSSCs technology includes these estimated values.

revealed linkages between these key sub-technologies, they linked the same IPC numbers to different time intervals and demonstrated the gradual evolutionary pathways for DSSCs sub-technologies over time. The main opinions and predictions are summarized in Table 5.

In Table 5, seven IPCs are listed as heighted sub-technology fields. As the H01M-10/40 is transferred to H01M 10/05-H01M 10/0587 and no longer existed in the 2010 edition IPC scheme, so the other 6 IPCs are selected to compare the real situation and previous opinions, as shown in Fig. 6(a). H01L-31/04 (semiconductor devices adapted as photovoltaics conversion devices) and H01M-14/00 (electrochemical current or voltage generators) share similar trends. They keep leading positions until 2012 and then decrease to a very low amount in 2016. There is no doubt they are the core research area within the DSSCs industry, but they cannot hold the leading position in the several years to come. H01G-09/20 (light-sensitive devices), as previously judged, advances at a relatively continuous growth rate to become the most prominent IPC in recent years. H01L-31/042 (PV modules or arrays of single PV cells) stands out for its impressive increase in 2013 and 2014, but comes across a sharp drop subsequently. H01L-51/42 (employs organic materials as the active part for solid state devices) has not attained rapid development. C09B-23/00 (methine or polymethine dyes, e.g. cyanine dyes) has not yet shown strongly in patent activity.

In addition to the IPCs identified by our previous research, some emerging IPCs warrant attention – see Fig. 6(b). The criteria for choosing target IPCs is based on the number of patents for the chosen IPCs reaching 160 or more, which corresponds to the minimum IPC activity presented in Fig. 6(a). It indicates that most of these chosen IPCs emerge after 2005, except for H01L-51/00 (Solid state devices using organic materials as the active part). H01L, which relates to semiconductor devices, is the biggest subordinate emerging research area in the field of DSSCs, and 6 IPCs belongs to this subclass, including H01L-31/18 (Processes or apparatus specially adapted for the manufacture or treatment of these devices or of parts thereof semiconductor devices), H01L-31/0224 (Electrodes of semiconductor devices), H01L-51/48 (Processes or apparatus specially adapted for the manufacture or treatment of such devices or of parts thereof solid state devices), H01L-51/44 (Details of solid state devices), H01L-51/46 (Selection of organic materials), and H01L-51/00. Besides, H01G, relating to basic electric elements such as capacitors, rectifiers, switching, light-sensitive or temperature-sensitive devices of the electrolytic type, is another noteworthy subclass. It includes H01G-09/04 (Electrodes of electrolytic capacitors) and H01G-09/042 (characterized by the material of electrodes). Specially, H01G-09/042 is the unique IPC that shows a strong growth trend in patents in 2015 and 2016.

In general, most evolutionary trends for sub-technology DSSCs fields heavily depend on the technology life cycle. In the early exploring stage, the foci are scattered and it is hard to pinpoint the potential components. When the technology enters the growth stages, the core devices, processes and apparatus get increased attention to promote the whole technology forward. When it comes to the maturity phase, the overall growth trends may suffer an obvious decrease but the material-related fields remain promising prospects for R&D and subsequent patenting. Therefore, when we make a prediction, the development stages should be carefully observed and the main technology functions should be identified and distinguished. Moreover, the new combinations of technologies (existing and/or emerging) and many socio-economic forces (e.g., fluctuations in demand, regulations, ethical or environmental concerns) may also change a developmental trajectory and technology filing evolutionary trends.



(a) The heighted IPCs in previous research

(b) The other emerging IPCs from current view

Fig. 6. Publication trends of leading DSSCs IPCs, 1991–2016.

4.3.2. The evolution of potential technology foci

One of our previous analyses on DSSCs using the FIP approach provided a framework for shaping the potential innovation pathways over a timeframe (Guo et al., 2012c). This framework helped to locate the obstacles and opportunities that are likely to facilitate or inhibit progress along a particular pathway. This framework sets out a prescribed procedure for analysis: the literature is reviewed first, followed by an initial database search. The database search results are text mined to identify local expertise. Face-to-face interviews with some of those experts provide input for the first evaluation of the analyses. Then, a workshop is conducted to focus on mapping likely innovation avenues following the process described and demonstrated by Robinson and Propp (2008). These expert workshops involve a wider spectrum of experts and stakeholders for more extended interactions (e.g., a full day). A key element of many future-oriented technology analyses is the expert forecasting workshop. These workshops provide a means of combining codified and tacit knowledge to explore the plausibility of various technology options. They also provide key intelligence for assessing the potential innovations that may stem from each option (Huang et al., 2012). In tandem, a multi-path map of the technology's future course is developed – in our case DSSCs. Such visualizations stimulate workshop interactions and create a framework for drawing out the intelligence held by the experts in the workshop–a scaffold upon which to locate their knowledge. The main ideas of the results from the analysis in (Guo et al., 2012c) are presented in Table 6.

In this paper, we attempt to validate the results previously derived based on the updated dataset. Usually, the “what” question is especially challenging. Some fielded records contain helpful content, such as keywords in paper abstracts and classification codes for patents (Newman et al., 2014). Hence, we first applied natural language processing (NLP) to extract terms and words in the merged titles and abstract fields of patents. We then followed “term clumping” steps to clean and consolidate topical content, mainly using a combination of thesauri and fuzzy matching routines (Zhang et al., 2014c). After selecting the main technology foci in four DSSCs sub-technologies, we made a matrix of these terms by publication year. Here, we only care about the materials and products in DSSCs for comparisons and updates.

In terms of the advances in materials R&D, the main technology foci of DSSCs materials in four sub-technologies for the period of 2001–2016 are presented in detail in Fig. 7. The color in the corresponding grid indicates the relative degree of boom for the whole period. From red to green, the degree is in descending order. We established that among the various nano-structured materials that are used as a semiconductor layer in DSSCs photoanodes, titanium dioxide (TiO2), zinc oxide (ZnO), and tin dioxide (SnO2) are still the most important materials, continuing from the early stage to now. But the developmental level of cadmium sulfide (Cds), copper indium diselenide (CIS), and cadmium telluride (CdTe) fell behind our previous predictions. In addition, we developed a sense that previous forecasts appeared rough, with few detailed messages, and were hard to trace. Thus, the time-series-based examination of sub-technologies offers an inspiring perspective to enhance forecasting for potential technology foci.

At the level of DSSCs products, previous analyses (Table 6) indicated that 3D solar cells and nanoparticle-based solar cells would likely emerge over the short-to-medium term, and that organic solar cells and quantum dot solar cells would blossom over the longer term. [Keep in mind that these data and their patterns are based on our DSSCs patent searches; that is, they concern these as sub-topics within DSSCs.] Fig. 8 presents the annual trends for nano-enhanced solar cell-related products. As shown, organic solar cells grew rapidly from 2008 but began to decrease from 2013, rather than continuing to develop. In fact, organic solar cell research began 30 years ago but has attracted significantly more scientific and economic interests over the last decade, triggered by a rapid increase in power conversion efficiency (Hoppe and Sariciftci, 2004). However, as many other new types of solar cells have emerged in recent years, its growth has turned into decline. Nanoparticle-based solar cells indeed saw remarkable gains over the past several years. In addition, the predicted trend for silicon thin-film solar cells and quantum dot solar cells were well informed and projected at the right levels. Nanoparticle cells have since seen a decline, but quantum dot solar cells have maintained a stable growth rate with a high possibility that they will continue to develop and maintain an important position in the future. The development of 3D solar cells has not met expectations and has not been widely explored, even though it shows promise for improvements in conversion efficiency by absorbing virtually all of the light.

Tracing the innovation pathways of potential technology foci offers an important tool set to approach real improvements in forecasting emerging topics and their potential applications. However, the comparative results show there is still a gap that cannot meet full expectations. On one hand, previous work like (Guo et al., 2012c) lacks the effective method to provide appropriate level content when facing the abstract record results that pertain to a particular technology. On the other hand, combining empirical with expert analyses seems promising to address “what” issues, but intelligibly clumped phrases are needed to appropriately provided for expert review to point out key topics and technologies for further scrutiny. Therefore, an effective method to extract technical content for technological intelligence turns out to be an alternative solution. For example, topic modeling appears to have utility to reduce the cycle time, the complexity, and analyst input required for a technology analysis (Newman et al., 2014). Such an approach presents an attractive scalability, suggesting the possibility to move beyond abstracts into full text analysis. However, such a method based on analytical software can offer help in most reducing time-consuming steps, but it still requires effective assessment by human efforts and domain knowledge.

Table 6
Ingredients of multipath exploration for DSSCs.

Goals	Present[a]	Short/medium term	Long term
Envisioned application areas	Grid-connected	Off-grid	Personal product
Anticipated potential product platforms	Conventional solar cells; Sillicon thin-film solar cells	3D solar cells; Nanoparticle-based solar cells	Organic solar cells; Quantum dot solar cells
Functionalities expected to made available	A large surface area could increase light absorption; Provide new film deposition methods to reduce cost	Large surface area could help charge separation; Multiple excition generation (MEG)	Tailor optical properties through its size
Nanostructures that are expected to be applied to solar cells	Nanoparticle; Quantum dot	Nanowise; Carbon nanotubes	
Advances in material R&D	Titanium dioxide (TiO2); Zinc oxide (ZnO); Tin dioxide (SnO2)	Cadmium sulphide (Cds); Copper indium diselenide (CIS); Cadmium Telluride (CdTe)	

Note: Here, “present” means that time is around 2010.

Technology	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Titanium dioxide	13	12	30	46	69	51	72	77	156	168	215	243	212	226	122	111
Zinc oxide	4	6	6	9	23	25	24	38	84	86	105	92	70	92	39	30
Tin oxide	2	5	9	5	18	26	13	19	43	56	47	57	42	53	31	17
Fluorine-doped tin oxide	0	1	1	4	9	11	12	16	42	53	47	64	40	47	30	49
Indium tin oxide	2	1	1	1	16	23	11	21	42	36	43	44	25	45	26	36
Silicon oxide	0	2	0	4	3	5	2	9	17	15	26	36	22	29	12	11
Zirconium oxide	1	3	1	4	8	6	5	5	19	13	25	25	23	26	9	9
Niobium oxide	1	3	2	4	10	10	9	7	27	12	23	23	19	16	3	5
Magnesium oxide	0	1	0	1	3	4	4	5	16	16	26	31	19	18	11	8
Oxide semiconductor electrode	1	3	4	6	3	5	9	8	14	3	11	13	7	5	4	1
Copper-indium-gallium-selenium	0	0	0	0	0	3	0	0	6	6	9	9	18	14	4	9
Antimony dope tin oxide	0	0	0	1	3	1	2	4	12	8	5	9	2	11	8	3
Gallium oxide-zinc oxide	0	0	0	0	1	2	3	1	6	8	12	7	4	6	8	3
Yttrium oxide	0	0	0	0	2	1	1	2	8	3	6	16	7	6	5	1
Calcium oxide	0	0	0	0	0	2	0	0	3	10	12	7	7	7	4	5
Lanthanum oxide	0	0	0	0	4	2	1	2	9	4	4	14	4	6	1	2
Antimony oxide	1	0	1	2	2	2	1	2	2	2	7	3	8	5	7	0
Aluminum zinc oxide	0	0	0	0	1	1	1	1	0	6	10	10	1	6	1	2
Cerium oxide	0	0	0	0	1	0	1	2	3	1	2	5	10	3	2	4
Indium zinc oxide	0	0	0	0	1	0	0	1	1	5	6	3	1	6	3	0
Lithium oxide	0	0	0	0	0	1	0	0	0	1	3	3	3	4	4	3
Stibium-doped tin oxide	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0

(a) Main Technology Foci of DSSCs Photoanodes, 2001-2016

Technology	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Organic dye	1	1	5	11	9	9	6	8	18	21	23	23	39	30	15	10
Ruthenium complex dye	3	1	0	0	1	0	4	2	7	9	8	7	6	5	5	6
Porphyrin-based dye	1	0	0	2	2	4	2	3	5	4	1	11	7	6	3	6
Cyanine dye	0	0	0	2	2	2	2	3	2	5	4	6	5	3	2	2
N719 dye	0	0	0	0	0	0	0	0	2	6	6	8	4	7	4	8
Solid state dye	0	0	0	0	0	1	1	3	0	7	7	7	4	5	7	2
Metal complex dye	3	1	2	1	2	2	0	1	1	2	2	3	3	10	2	6
Fluorescent dye	1	2	0	2	1	3	6	4	4	4	2	0	3	0	0	0
Merocyanine dye	2	0	2	1	1	4	0	0	3	4	3	5	5	1	1	2
Black dye	0	0	0	0	0	2	0	2	3	4	3	0	1	6	2	0
Phenothiazine dye	0	0	0	0	0	0	0	1	0	0	3	5	2	4	1	2
Natural dye	0	1	0	0	0	0	0	0	2	0	2	2	3	2	4	0
Fluorine based dye	0	0	0	0	0	0	0	0	0	1	3	2	1	0	2	0
N3 dye	0	0	0	0	0	0	0	0	2	1	0	0	2	1	2	0

(b) Main Technology Foci of DSSCs Sensitizers, 2001-2016

Technology	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Solid electrolyte	0	0	2	4	4	8	3	4	11	11	18	15	9	5	4	9
Liquid electrolyte	0	0	0	0	3	0	2	1	5	4	6	4	6	8	1	4
Non-aqueous electrolyte	0	0	0	3	3	5	2	1	3	1	1	1	1	1	0	1
Polymer electrolyte	0	0	0	2	1	0	1	3	0	2	1	4	3	2	1	0
Gel electrolyte	0	0	0	0	0	0	1	2	0	0	2	2	2	1	1	0
Gel-like electrolyte	0	1	0	0	0	0	0	0	0	2	3	2	1	0	0	1
Quasi-solid electrolyte	0	0	0	0	1	0	3	1	0	0	0	1	1	1	1	0
Salt electrolyte	0	0	0	0	0	0	1	0	5	0	0	1	1	0	0	0

(c) Main Technology Foci of DSSCs Electrolytes, 2001-2016

Technology	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Tungsten electrode	2	2	2	3	14	6	15	12	33	17	28	46	32	41	11	28
Molybdenum electrode	2	0	0	1	4	3	2	2	10	6	12	19	18	18	11	6
Platinum electrode	0	0	1	1	2	1	3	4	11	19	7	9	16	8	10	13
Metal electrode	0	0	0	0	0	2	1	3	3	8	10	16	13	5	2	1
Carbon electrode	0	0	0	2	1	0	1	2	2	5	2	3	5	3	1	1
Inorganic compound electrode	0	0	1	0	0	1	0	2	0	2	6	4	4	5	1	1
Conductive polymer electrode	0	0	0	0	1	0	1	0	1	2	0	0	0	1	1	2
Hybrid electrode	0	0	0	0	0	0	0	1	0	0	0	1	2	1	0	0

(d) Main Technology Foci of DSSCs Counter-electrodes, 2001-2016

Fig. 7. (a). Main technology foci of DSSCs photoanodes, 2001–2016, (b). Main technology foci of DSSCs sensitizers, 2001–2016, (c). Main technology foci of DSSCs electrolytes, 2001–2016, (d). Main technology foci of DSSCs counter-electrodes, 2001–2016.

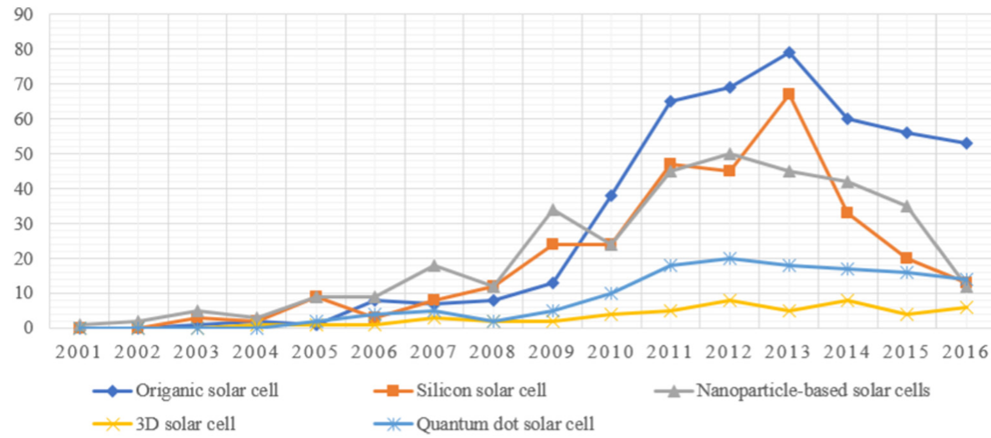


Fig. 8. Growing trends of solar cell-related products based on insights from DSSCs patents.

5. Conclusions and discussions

The paper proposes a framework for assessing data-driven technology forecasting and uses that framework to revisit our previous research on DSSCs using an updated patent dataset. After addressing the technology life cycle to locate whether the technology has progressed through developmental phases as previous indicated, we compared the basic technology profiling and validated enhanced technology detection. We conducted a comparative empirical study to contrast the results in terms of the technology's stage in its country/regional focus and the prominent actors. We then attempted to identify role changes among leading, emerging and declining status as DSSCs progress through various stages. In addition, we further explored evolution of technological sub-fields and technological foci to figure out what are the differences. We seeked for what factors may cause the differences when the results shows that some preceding predictions correspond to actual performance; but others do not.

We conclude that a number of factors account for these differences: First, data quality is the foundation of data-based technology forecasting, including its veracity and completeness. Veracity can be enhanced by using an appropriate search strategy on a reliable data source. But insufficient data is an innate problem that cannot be totally avoided. For example, inaccuracies in our forecasts on DSSCs's stage in its lifecycle in a previous study were in part because we could not always obtain the most recent data. Therefore, frequent monitoring (data updating) is a recommended way to deal with this imperfection. Second, technology forecasting methods are empirical indicators of sociotechnical changes, and no approach is perfect. We cannot rely heavily on a single method, but rather aggregate diverse approaches with complementary strengths need to mitigate the limitations of any method alone. Third, future-oriented analyses are characterized by complexity and dynamism, so less emphasis needs to be placed on the leading actors or trends in the current stage, in favor of the emergent actors and trends, which are more likely to influence the near future.

Although the development of technology follows a certain path dependence, the evolutionary trend sometimes "jumps," rather than tracking neatly, due to various uncertain external factors and somewhat random mutations along the evolutionary path. In the "Managing the present from the future" section of *Forecasting and Management of Technology*, the authors give a dozen recommendations for technology forecasting. We agree with their thesis that, "The future is very much an open system with fuzzy, impenetrable boundaries in both space and time. Images of the future must accommodate uncertainty and be adaptable, yet provide focal points to guide present actions" (Roper et al., 2011b). Technology forecasting offers a relevant opportunity in this direction and is currently an up-and-coming area of research. Forecasters can learn much from re-analyzing past predictions, and there is value in paying more attention to the retrospective by assessing what we have done as a means to improving what we should and will do going forward.

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