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Full Length Research Paper

Technology forecasting of new clean energy: The example of hydrogen energy and fuel cell

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Due to energy shortage, global warming and climate change, balanced development of energy security, economic growth, and environmental protection (3Es) has become a major energy policy issue and prompted the development of low-carbon economies. The goals of exploiting new clean energies, improving the efficiency of conventional energy sources, and improving renewable energy technologies have gathered considerable attention of governments worldwide. Among the many clean energies, hydrogen energy plays an important part in new clean energy fields nowadays. However, little has been done in discussing the technology forecasting for the hydrogen energy development. Therefore, this study predicts the technological S-curves for hydrogen energy and fuel cell technologies by integrating bibliometric and patent analysis into the logistic growth curve model, which includes generation, storage, proton exchange membrane fuel cell (PEMFC), solid oxide fuel cell (SOFC) and direct methanol fuel cell/direct alcohol fuel cell (DMFC/DAFC). Empirical analysis is via an expert survey and co-word analysis using the USPTO database to obtain useful data. The results demonstrate that technologies for generating and storing hydrogen have not yet reached technological maturity, and the fuel cell technology is either in the mature stage or approaching maturity.

Key words: Hydrogen energy, technology forecasting, S-curves, bibliometric analysis, fuel cell.

INTRODUCTION

The rapid growth in consumption of fossil fuels has accelerated their depletion. Fossil fuel reserves are diminishing rapidly across the world, intensifying the stress on existing reserves day-by-day due to increased demand. Not only that, fossil fuels, presently contributing to 80% of world primary energy, are inflicting enormous impacts on environment. Climatic changes driven by human activities, in particular the production of greenhouse gas emissions, directly impact the environment. A secure and accessible supply of energy is thus very crucial for the sustainability of modern societies (Kothari et al., 2008). Hydrogen energy is a valuable high-quality, non-polluting and safety fuel (Beccali et al., 2008). In addition, hydrogen production represents one of the most promising solutions for solving the problem of intermittence in the power production by renewable sources by reducing local impacts of energy conversion and diverting it to several final uses. Unlike the fuels used today, it is free of carbon, as a result, no climate-influencing carbon dioxide is released during combustion or use in a fuel cell (Gasafi et al., 2008). Thus, it has long been included in the International Energy Agency (IEA) plan as a major component of clean energy systems and is predicted to account for 50% of total energy consumption by 2050.

Hydrogen energy technologies encompass hydrogen production, storage and delivery and can be applied to fuel cells and internal combustion engines. The hydrogen energy industry is currently focused on chemical, petrochemical, metallurgy and electronic processes, with applications largely in experimental and emerging stages. Many companies worldwide have invested in hydrogen energy and now offer a wide variety of products that use hydrogen energy. However, none of these products has reached the scale of mass production. Conversely, most hydrogen energy products on the market are substitute products; that is, explain what a substitute product is. Before consumer demand for such substitute products

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increases and their costs reduce, commercial scale demand is not foreseeable in the near future. Therefore, understanding the technological development of hydrogen energy and predicting its future trends will prove useful when formulating strategies for hydrogen energy development.

During the past several decades, there has been growth in the number of growth curve methods for examining the development of technology, and the subsituation of technology. Growth curve method involves fitting a growth curve to a set of data on technological peformance, then extrapolating the growth curve beyond the range of the data to obtain an estimate of future performance (Cheng et al., 2008; Frank, 2004; Meade and Islam, 1998; Porter et al., 1991; Watts and Porter, 1997). However, it is rather difficult to forecast the development of technologies as there are rare historical data available, such as in those new clean energies fields. Therefore, this study would use the bibliometric analysis to gain the useful data for growth curve model to investigate the technology forecasting of hydrogen energy technologies, which includes generation, storage, the proton exchange membrane fuel cell (PEMFC), solid oxide fuel cell (SOFC), and direct methanol fuel cell/direct alcohol fuel cell (DMFC/DAFC).

The remainder of this paper is organized as follows. Section II provides a literature review; Section III describes the methodology and data sources; Section IV presents the empirical results; and Section V concludes the study.

LITERATURE REVIEW

In recent years, the technology forecasting analysis technique has been adopted as the analytical tool for evaluation of technological performance. Schilling and Esmundo (2009), who analyzed renewable energies using such a technology S-curve perspective, identified some important implications for both governments and industry. Their empirical analysis was based on data for government R&D investment and technological improvement (in the form of cost reductions). Schilling and Esmundo demonstrated that both wind energy and geothermal energy are poised to become more econo-mical than fossil fuels within a relatively short time frame. Additionally, the evidence further suggests that R&D for wind and geothermal technologies has been underfunded by governments compared with funding for solar technologies, and government funding of fossil fuel technologies may be excessive given the diminishing perfor-mance of those technologies. Chu et al. (2009) compared the performance of three conventional models, namely, the Gompertz, Logistic and Bass models, to identify the most appropriate model and identify the forces driving the diffusion rate. Empirical results indi-cated that the Logistic model performed best. Network externalities, which this study shows to be the same as the imitation effect in superiority of the Bass model, explains the Logistic model.

Cheng and Chen (2008) applied the growth curve method to investigate the technological performance of nano-sized ceramic powders. That study applied bibliometric analysis to the engineering index (EI) database and United States Patent and Trademark Office (USPTO) database to acquire useful data. The principal finding was that nanosized ceramic powders were all in the initial growth periods of their technological lifecycle. To summarize, this study found that growth curve methods were suitable for examining the technological development and substitution.

However, predicting the development of technologies is rather difficult as historical data are typically unavailable for new clean energies. Bibliometric analysis is defined by Norton (2001) as the measurement of literatures and texts. The approach is to capture some of the information inherent in the content and patterning of the literature. Bibliometric analysis uses counts of publications, patents, or citations to measure and interpret technological advances (Watts and Porter, 1997). Historically, bibliometric analyses have been used to trace back academic journal citations. Nowadays, bibliometric analysis can be used to understand the past and even potentially to forecast the future (Cunningham, 1997; Morris et al., 2002; Narin et al., 1994). Three major types of bibliometric analysis have emerged, which includes citation analysis, patent analysis, and publication analysis (Garfield et al., 1978). Citation analysis examines referencing patterns among papers and/or patents to detect seminal contributions and interaction patterns, and even to forecast emerging research areas. Patent analysis relates patenting activity to profile company interests and industry trends. Publication analyses take articles and as such tell indicators of R&D activities (Garfield, 1978).

The bibliometric analysis, which was recently applied to solve this problem, can provide an interesting alternative data source for quantitative evidence of R&D activity and text materials (Bengisu and Nekhili, 2006; Martino, 2003; Watts and Porter, 1997, 2003). To summarize, bibliometric analysis could provide a nicely accessible and cost-effective data or information. It helps to explore, organize and analyze amounts of historical data helping researchers to identify “hidden patterns” that may help researchers in the technology forecasting and decision making process (Bengisu and Nekhili, 2006; Watts and Porter, 1997).

Therefore, this study uses the bibliometric analysis to collect useful data for the growth curve model to forecast the development of hydrogen energy and fuel cells, including the generation and storage of hydrogen energy, the PEMFC, SOFC, and DMFC/DAFC. Besides, this study assumes diffusion of hydrogen technologies, as measured by number of patents and publications, following the well known S-curve of natural growth.

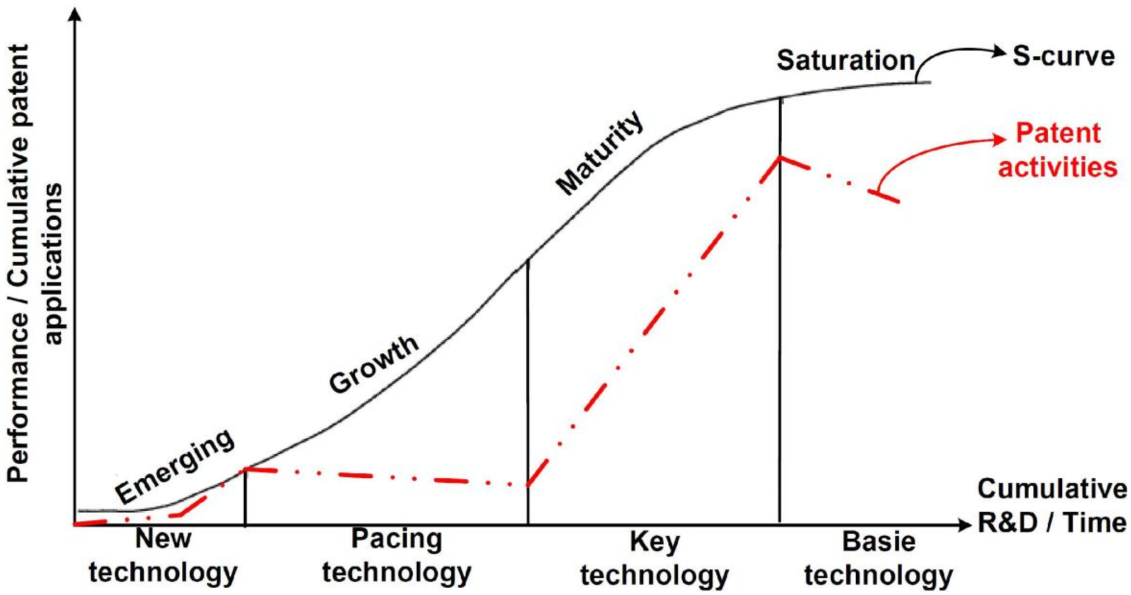

Figure 1. Scheme of integration for technological S-curve and patent activities.

METHODOLOGY AND DATA SOURCES

The growth curve model

Many technologies exhibit an S-curve in their performance improvement over their lifetimes (Ayres, 1994; Christensen, 1993, 1994; Foster, 1986; Twiss, 1992). When the performance of a technology is plotted against the amount of effort and money invested, it typically shows slow initial improvement, then accelerated improvement, and then diminishing improvement (Figure 1). Forecasting using the growth curves method is based on parameter estimation of the lifecycle curve of a technology. The method is helpful for estimating the level of technological growth or decline at each stage in the lifecycle and in predicting when a technology will reach a particular stage (Frank, 2004; Watts, 1997; Meade and Islam, 1998; Porter et al., 1991; Bhargava, 1995). Figure 1 shows the S-curve concept and patent activities over the technological lifecycle, which has four developmental stages (Ernst, 1997). The emerging stage is characterized by a relatively slow technological growth compared with the amount of R&D effort. During the growth stage, marginal technological progress divided by cumulative R&D expenditures is positive, and is negative during the mature stage. During the saturation stage, small technological performance improvements are gained only through considerable R&D efforts.

The most commonly used formulation of the Logistic growth curve or simply the well known S-curve is described by the following equation (Meyer et al., 1999), which was the most popular growth curve model in technology forecasting field.

$$P\left(T\right)=\frac{K}{1+E^{-(\alpha(T-\beta))}} \qquad (1)$$

where

P(t): The variable representing performance.

K: The capacity of the population, showing how large the population *P* will become.

α: The "width" or "steepness" of the sigmoid curve.

β: The midpoint of the growth trajectory.

Equation (1) produces the familiar S-shaped curve. Note that three parameters are needed to fully specify the curve, *α*, *β*, *k*. The growth rate parameter, *α*, specifies the "width" or "steepness" of the sigmoid curve. It is often helpful replacing α with a variable that specifies the time required for the trajectory to grow from 10 to 90% of the limit *k*. a period which is called the characteristic duration, or *dt* (Meyer et al., 1999). Through simple algebra, the characteristic duration is related to *α* by $DT=\frac{\mathrm{LN}\left(81\right)}{\alpha}$. The parameter *dt* is usually more useful than α for the analysis of historical time-series data, because the units are easier to appreciate. The parameter *β* specifies the time when the curve reaches 1/2 *k*, or the midpoint of the growth trajectory, often re-labeled t_m. The parameter *k*, as discussed, is the asymptotic limit that the growth curve approaches, that is, market niche or carrying capacity. The logistic model is symmetric around the midpoint t_m (Meyer et al., 1999). The three parameters *k*, *dt*, and t_m define the parameterization of the logistic model used as Equation (2):

$$P\left(T\right)=\frac{K}{1+E^{-\frac{\mathrm{LN}(81)}{DT}\left(T-T_M\right)}} \qquad (2)$$

dt: the characteristic duration of the curve, i.e., the time needed for *P* to grow from 10% to 90% of *k*.

t_m*:* The midpoint of the curve at which 50% of *k* is reached.

Using Loglet Lab software, which can fit growth processes using one or more S-curves and a possible initial displacement, a logistic fit is produced that is tested against actual world data and utilized to make projections about the global trend.

Data sources

As this study investigates the technology forecasting of hydrogen energy and fuel cell, study data were collected from the online

Table 1. Details of expert survey.

Name	Title	Position and Department
Chiang KC	Patent Engineer	Institute of Law for Science and Technology, National Tsing Hua University
Fan CT	Professor	Institute of Law for Science and Technology, National Tsing Hua University
Hwang BJ	Professor	Department of Chemical Engineering, National Taiwan University of Science and Technology
Lin CW	Professor	Department of Chemical and Materials Engineering, National Yunlin University of Science and Technology
Lin SD	Professor	Department of Chemical Engineering, National Taiwan University of Science and Technology
Yang MC	Professor	Department of Chemical Engineering, National Cheng Kung University

Table 2. Background set for patent searching.

Database source		USPTO (Issued patents)
Time interval		**1969 ~ 2008**
Field code		**TTL(title), ABST(abstract), ACLM(claims)**
Keyword	Generation	"Hydrogen production" OR "Production of hydrogen" OR "hydrogen formation" OR "formation of hydrogen" OR "hydrogen manufacture" OR "hydrogen manufacturing" OR "manufacturing of hydrogen" OR "hydrogen generation" OR "generation of hydrogen" OR "hydrogen generator"
	Storage	"Hydrogen storage" OR "Storage of hydrogen" or "hydrogen storage" OR "storage of hydrogen" OR "hydrogen generator"
	PEMFC	"Proton exchange Membrane" OR "ion exchange Membrane" OR "polymer electrolyte" OR "solid polymer") ANDNOT (Methanol OR Alcohol)
	SOFC	"Ion conducting ceramics" OR "Oxygen ion conductor" OR "oxide membrane" OR "oxide electrolyte" OR "mixed oxides" OR "inorganic electrolyte" OR "ceramic electrolyte"
	DMFC/DAFC	(Methanol OR Alcohol) AND NOT Reforming

USPTO database, which was first built in 1969. The data collected covered the period of 1969 to the present. This study first determined data frequencies using bibliometric analysis. Data were then input into Loglet Lab software to generate logistic growth curves. Finally, this study obtained technology growth curve data for the saturation, midpoint, and growth of time for analyzing technology developments and tendencies. Additionally, Co-word analysis is the most common analytical tool for inferring a cognitive structure from words appearing together and extracting multiword phrases or keywords frequencies (Watts and Porter, 1997). Therefore, this study also used Co-word analysis to infer the cognitive structure of words appearing together and extracting multiword phrases or keywords frequencies based on an expert survey (Tables 1 and 2). The cumulative frequencies of data for fitting logistic growth curves can be used to determine the technological performance of hydrogen energy and fuel cells.

In addition, in the growth curve model, determining fit precision is very important. By applying a technique called parametric bootstrapping (that is, the bootstrap method) one can compute a confidence interval for each parameter. The bootstrap method is a means of re-creating and re-sampling data using Monte Carlo methods (Efron and Tibshirani, 1993; Efron, 1979). The bootstrap method synthesizes a dataset by re-sampling residuals from an initial fit, and fitting a curve to the new dataset. The Central Limit Theorem (CLT) assumes that bootstrapped parameter estimates are normally distributed around a sample mean. From these sets one can compute confidence intervals for parameters. Loglet Lab repeats this process of synthesizing and refitting 200 times, producing a sample dataset of 200 values for each parameter, from which their respective confidence intervals are computed. From the confidence intervals of a parameter, it would form a confidence region containing the set of all curves corresponding to all values of a given parameter. Traditionally, bootstrap confidence intervals have been determined using various methods (Efron, 1979), such as the standard bootstrap method, percentile bootstrap method, and biased-corrected percentile bootstrap method. This study applied percentile bootstrap analysis to establish bootstrap confidence intervals.

EMPIRICAL RESULTS

Using Loglet Lab software and patent publications data, logistic fits are produced for hydrogen energy and fuel cell technologies. Figures 2 - 6 present growth curves based on actual data and fitted models for the period 1969 - 2008 (as of December of each year).

Take the example of "hydrogen generation technology." Investigating the development activities of hydrogen generation technologies, the numbers of publications of those technologies were obtained from the USPTO database for the period 1969 - 2008 year. Using the keywords "hydrogen production" and "production of hydrogen" in the title (TTL), abstract (ABST), and claims (ACLM) yielded 1,448 publications for this period. The cumulative publications data for hydrogen generation technologies were modeled using the logistic growth

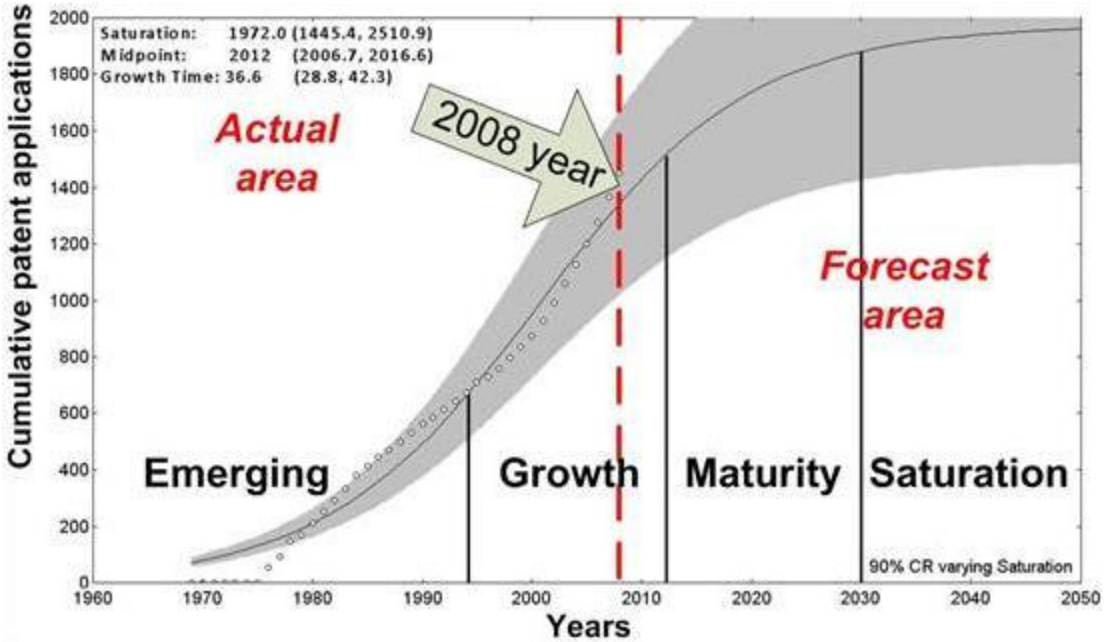

Figure 2. The growth curve of hydrogen generation technology by using the logistic model: the number of publications.

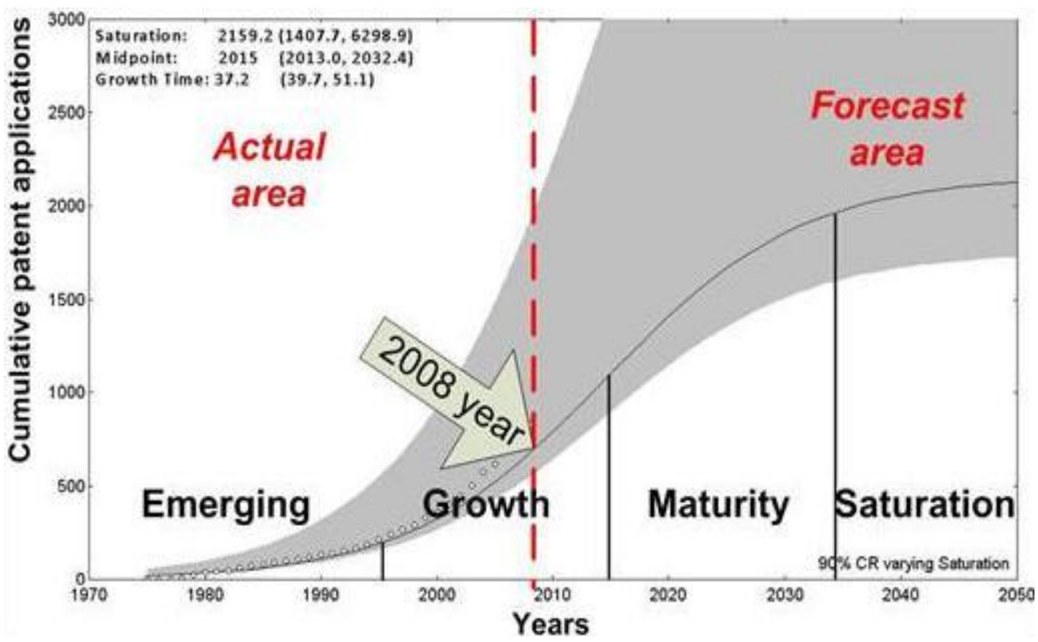

Figure 3. The growth curve of hydrogen storage technology by using the logistic model: the number of publications.

curve function, as shown in Figure 2. From Figure 2, the significant information about the technological lifecycle of hydrogen generation can be obtained. The midpoint of the hydrogen generation growth curve was at the year 2012, the duration of growth time was 36.6 years; the drop in publication activity in 2012 may also indicate that the technology growth curve passes an inflection point. For the periods 1994 - 2012 and 2012 - 2030, the growth curve was divided into growth and mature stages. The saturation number of publications of the cumulative hydrogen generation might be attained to 1972.0. Table 3 summarizes the results for other cases. A look into

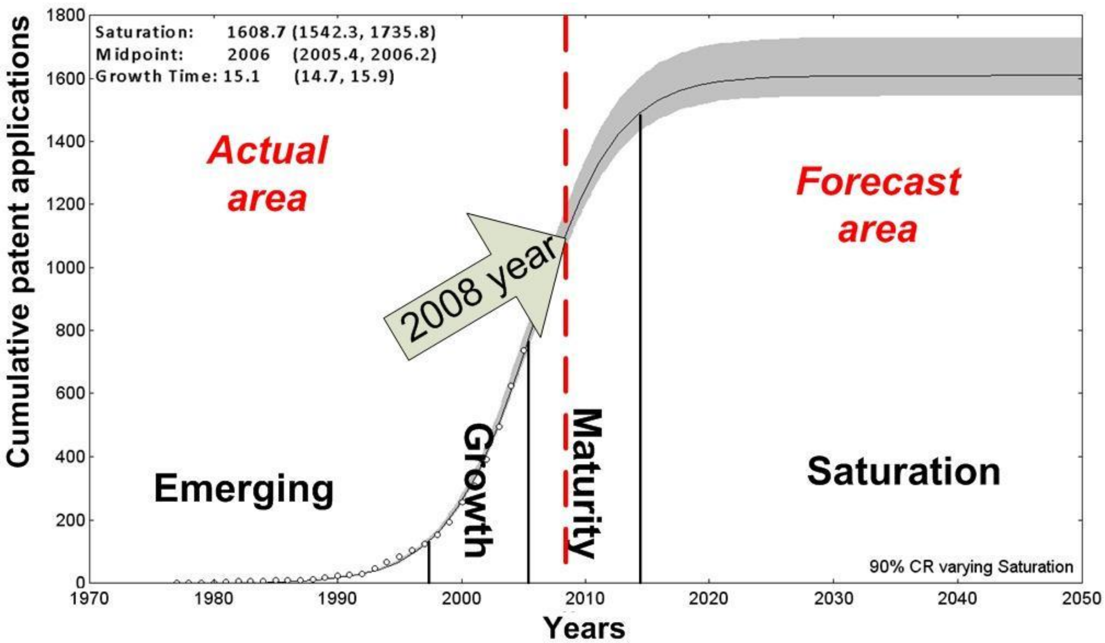

Figure 4. The growth curve of PEMFC technology by using the logistic model: the number of publications.

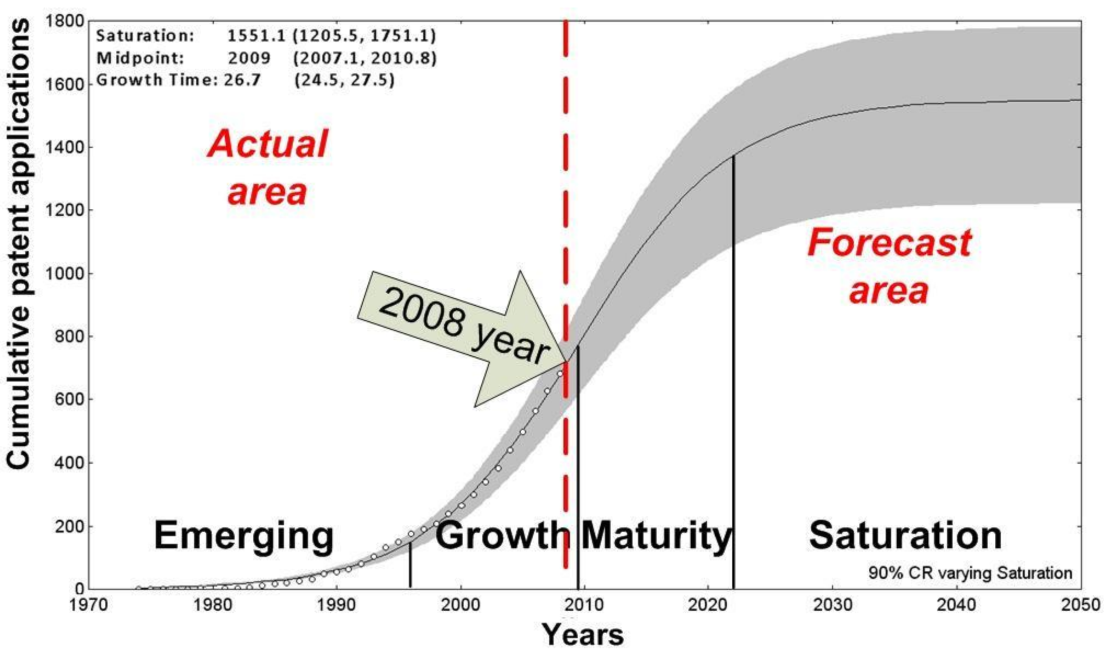

Figure 5. The growth curve of SOFC technology by using the logistic model: the number of publications.

changes in the bootstrap analysis (shadow area in Figure 2) shows that 90% bootstrap confidence intervals on estimated parameters for growth of "hydrogen generation technology." The intervals of estimated parameters were then obtained; the "saturation" number was 1445.4 - 2510.9, the "midpoint" was 2006.7 - 2016.6, and "growth time" was 28.8 - 42.3 years. Table 4 summarizes sensitivity analysis results for other cases.

Conclusions

New clean energies have been recognized as drivers of today's rapidly changing environments. Hydrogen

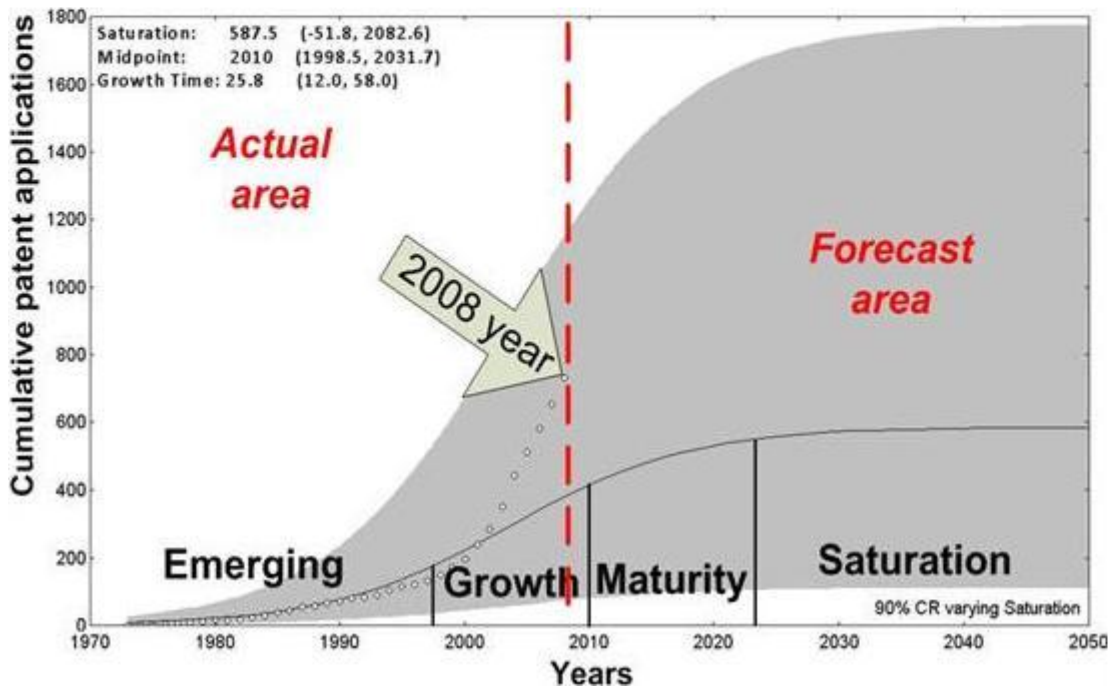

Figure 6. The growth curve of DMFC/DAFC technology by using the logistic model: the number of publications.

Table 3. Life cycle stage of all cases.

Cases	Years				Saturation
	Emerging	Growth	Maturity	Saturation	
Generation	1969	1994	2012	2030	1972.0
Storage	1975	1996	2015	2034	2159.2
PEMFC	1977	1998	2006	2014	1608.7
SOFC	1974	1996	2009	2022	1551.1
DMFC/DAFC	1973	1997	2010	2023	587.5

energies now play important roles in the new clean energies field. However, few studies have forecasted new clean energies development. This study applied the Logistic growth curve model to investigate the technological performance of hydrogen energy, which includes its generation and storage, and the PEMFC, SOFC, and DMFC/DAFC. Empirical analyses are based on an expert survey and Co-word analysis of the USPTO database to obtain useful data. This study is an important reference for technology forecasting and development of the new clean energies field. Three major findings could be made as follows:

Firstly, hydrogen production and hydrogen storage technologies are still currently in their growth stage. This is primarily because hydrogen production technologies are analyzed in terms of water decomposition, light decomposition, and the reforming reaction, with an enormous number of patents for myriad technologies. This means that a patent search would generate both well-developed and new hydrogen production technologies. Hydrogen storage technologies have not reached the mature stage and are developing at a slower pace than generation technologies. This is mainly because the requirements for hydrogen storage systems are stringent and current development has hit a bottleneck. Notably, analytical results indicate that hydro-gen storage technologies are in the growth stage. In summary, the timelines for hydrogen production and storage technologies will be long before reaching the mature stage.

Secondly, fuel cell technology is either in the mature stage or approaching maturity. However, fuel cell technology is still constrained by challenges associated with hydrogen storage and production. The commercialization of fuel cell vehicles and communication, computer, and consumer (3C) products will likely be delayed due problems related to hydrogen production and storage.

Table 4. Parameters and accuracy of the logistic fits for all technologies.

	Logistic fits												Congruence analysis	
	Midpoint (T_M) [years]				Growth time (DT) [years]				Saturation (K) [numbers]				R^2	Significance[d]
	Value[a]	Min[b]	Max[b]	Error[c]	Value[a]	Min[b]	Max[b]	Error[c]	Value[a]	Min[b]	Max[b]	Error[c]		(Prob. > F)
Generation	2,012	2,006.7	2,016.6	0.002	36.6	28.8	42.3	0.184	1,972.0	1,445.4	2,510.9	0.270	0.875	0.000
Storage	2,015	2,013.0	2,032.4	0.005	37.2	39.7	51.1	0.153	2,159.2	1,407.7	6,298.9	1.133	0.892	0.000
PEMFC	2,006	2,005.4	2,006.2	0.000	15.1	14.7	15.9	0.040	1,608.7	1,542.3	1,735.8	0.060	0.989	0.000
SOFC	2,009	2,007.1	2,010.8	0.001	26.7	24.5	27.5	0.056	1,551.1	1,205.5	1,751.1	0.176	0.949	0.000
DMFC/DAFC	2,010	1,998.5	2,031.7	0.008	25.8	12.0	58.0	0.891	587.5	-51.8	2,082.6	1.817	0.977	0.000

[a] Estimated by logistic growth method.
[b] Estimated by the bootstrap method with 90% confidence level.
[c] Estimated by the ratio of the average distance of the parameter value from its estimated minimum and maximum to the parameter value.
[d] Model congruence at significant at the 5% level. All tests are statistically significant with p-values < 0.05.

In addition to technological barriers, issues of product substitution and high price are addi-tional obstacles. Thus, hydrogen energy products will likely not be commercialized until 2030 or later.

Finally, the bibliometric analysis was proposed as the simple and efficient tool to link the science and technology activities and to obtain quanti-tative and historical data for helping researchers in technology forecasting, especially in rare histo-rical data available fields, such as the new clean energies fields.

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