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Technology life cycle analysis method based on patent documents

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ABSTRACT

To estimate the future development of one technology and make decisions whether to invest in it or not, one needs to know the current stage of its technology life cycle (TLC). The dominant approach to analysing TLC uses the S-curve to observe patent applications over time. But using the patent application counts alone to represent the development of technology oversimplifies the situation. In this paper, we build a model to calculate the TLC for an object technology based on multiple patent-related indicators. The model includes the following steps: first, we focus on devising and assessing patent-based TLC indicators. Then we choose some technologies (training technologies) with identified life cycle stages, and finally compare the indicator features in training technologies with the indicator values in an object technology (test technology) using a nearest neighbour classifier, which is widely used in pattern recognition to measure the technology life cycle stage of the object technology. Such study can be used in management practice to enable technology observers to determine the current life cycle stage of a particular technology of interest and make their R&D strategy accordingly.

1. Introduction

The rapidly changing economic environment and increasingly fierce competition require companies to be innovative, both in their products and marketing strategies, if they are to flourish. A successful product must balance three components: technology, marketing, and user experience [1]. Technology plays a key role among these three components [2]. Before the product strategy is formulated, a technology strategy must be developed to provide competitive products, materials, processes, or system technologies [3]. The first step for devising a technology strategy is to decide if the technology is worth the investment. How will the technology develop in the future? Will the technology flourish in the future or will it decline? To answer these questions, one should know the current life cycle stage of the technology in order to estimate future development trends to make informed decisions on whether to invest in it or not.

Within the Future-oriented Technology Analysis (FTA), technology forecasting traces back to the 1950's [4]. One of its half-dozen or so basic techniques, dating from that time at least, is trend analysis. This includes both historical time series analyses and fitting of growth models to project possible future trends [5]. Most trend projection is "naïve" — i.e., fitting a curve to the historical data under the assumption that whatever forces are collectively driving the trend will continue into the future unabated. It follows that such projection becomes increasingly precarious as the future horizon is extended beyond a few years.

Another important technology forecasting technique [6] is the use of analogies. Herein, one anticipates growth in an emerging technology based on the pattern of growth observed in a somewhat related technology. The stronger that relationship, the more likely the pattern will pertain.

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Another important predecessor approach upon which we draw is the identification of Technology Readiness Levels (TRLs). The U.S. military, especially the Air Force, has made use of this categorization of technology development to help identify current status and future prospects. Nolte et al. [7] overview the 7-level TRL and how to estimate this. The U.S. National Aeronautics and Space Administration (NASA) uses a 9-level version [8]. When a complex technical system incorporates a number of emerging technologies, use of TRLs has proven helpful in designing a viable new system. The key notion is that progress is likely, but precise anticipation of when a given advanced technology will be ready for application is precarious. Such a cautionary notion should be recognized for our approach developed here also.

The concept of the technology life cycle (TLC) was presented by Arthur [9] to measure technological changes. It includes two dimensions — the competitive impact and integration in products or process — and four stages. According to Arthur's definition, the characteristic of the emerging stage is a new technology with low competitive impact and low integration in products or processes. In the growth stage, there are pacing technologies with high competitive impact that have not yet been integrated in new products or processes. In the maturity stage, some pacing technologies turn into key technologies, are integrated into products or processes, and maintain their high competitive impact. As soon as a technology loses its competitive impact, it becomes a base technology. It enters the saturation stage and might be replaced by a new technology. According to this definition, Ernst [10] developed a map to illustrate TLC (Fig. 1).

The dominant approach to analysing TLC with an S-curve is to observe technological performance, either over time or in terms of cumulative R&D expenditures. But using one indicator only to present technological performance would be problematic. A research team from MIT [11] studied the development trends of power transmission technology and aero-engine technology by S-curve modelling. The results showed that the S-curve with a single indicator was not reliable and might lead the research in the wrong direction. They suggested considering multiple indicators to measure technological development and to make business decisions.

Usually, patent application activity is tracked as a TLC indicator for the S-curve analysis [10,12,13]. But using patent application counts alone to represent the development of technology oversimplifies the situation. Accordingly, some multiple indicators are used to measure TLC. Watts and Porter [14] have introduced nine indicators that look at publications of different types during the technology life cycle. Reinhard et al. [15] tested seven indicators related to patents. Table 1 shows the indicators listed in the two papers. These papers studied the indicators that would have different performance based on the changes of technology. Separately, the indicators can serve to measure technological changes. In this paper, we focus on combining multiple indicators to calculate the life cycle stages for an object technology and hope that would help decision makers estimate its future development trends.

2. Methodology

The model that we build to calculate the TLC for an object technology includes the following steps: first, we focus on devising and assessing patent-based TLC indicators, then we choose some technologies (training technologies) with identified life cycle stages, and finally we compare the indicator features in training technologies with the indicator values in an object technology

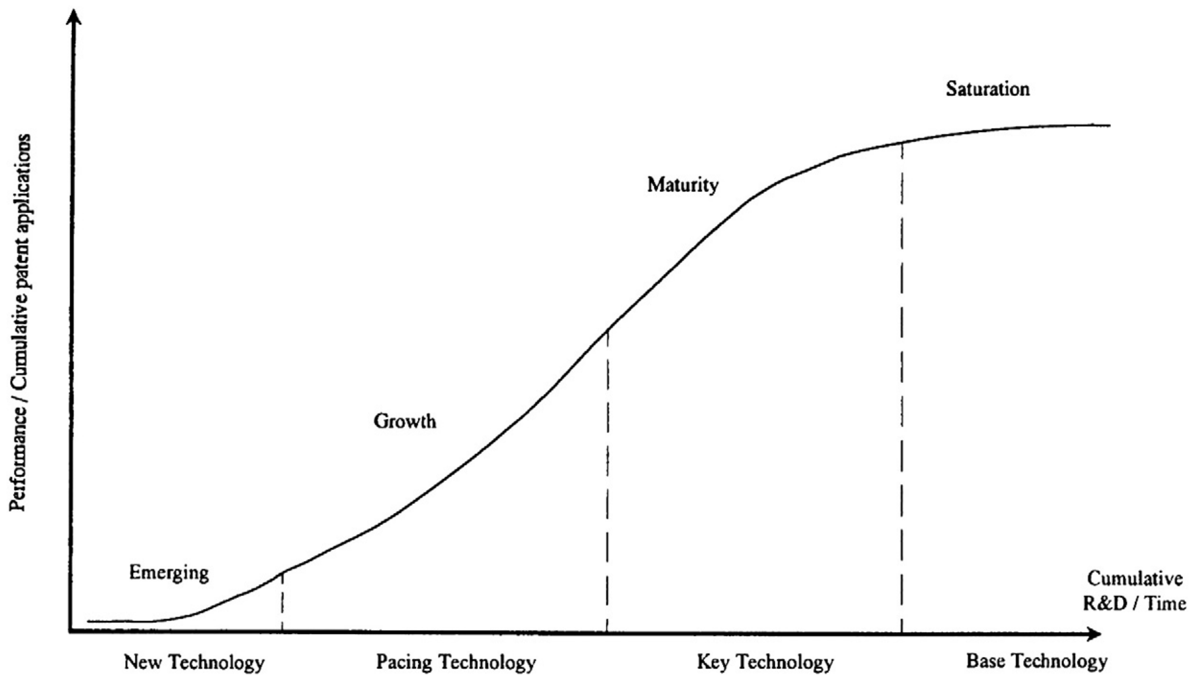

Fig. 1. The S-curve concept of technology life cycle.

Table 1
Technology life cycle indicators by former researchers.

Author	Indicator
Robert J Watts, Alan L Porter [14]	Number of items in databases such as Science Citation Index
	Number of items in databases such as Engineering Index
	Number of items in databases such as U.S. patents
	Number of items in databases such as Newspaper Abstracts Daily
	Issues raised in the Business and Popular Press abstracts
	Trends over time in number of items
	Technological needs noted
	Types of topics receiving attention
	Spin-off technologies linked
Reinhard Haupt, Martin Kloyer, Marcus Lange [15]	Backward citations
	Immediacy of patent citations
	Forward citations
	Dependent claims
	Priorities
	Duration of the examination process
	Data base requirements

(test technology) via the nearest neighbour classifier, which is widely used in pattern recognition, in order to measure the technology's life cycle stages. The research framework is designed as follows (Fig. 2).

2.1. Indicators and data source

The most fundamental and challenging task is to select suitable indicators and data sources. In a recent work [16], we have compiled candidate patent indicators from multiple sources. Thirteen indicators are selected for TLC assessment (Table 2). All the data of the indicators are extracted by priority year (the first filing date year for a patent application), except the first indicator.

In this research, we choose the Derwent Innovation Index (DII) as the data source and VantagePoint (VP) for data cleaning and extraction. Matlab 2010b is used for implementing the algorithms.

2.1.1. Application and priority

Usually, three kinds of dates are included in the DII database: application year, priority year, and basic year. The basic year has no legal meaning, but only represents the year in which DII obtained the patent documents. Currently, most of TLC related literatures are based on application year [15,17–20]. But the priority year presents the first time an invention has been disclosed. So in this paper, we choose the other two indicators to measure the development of technology: we count the number of patents

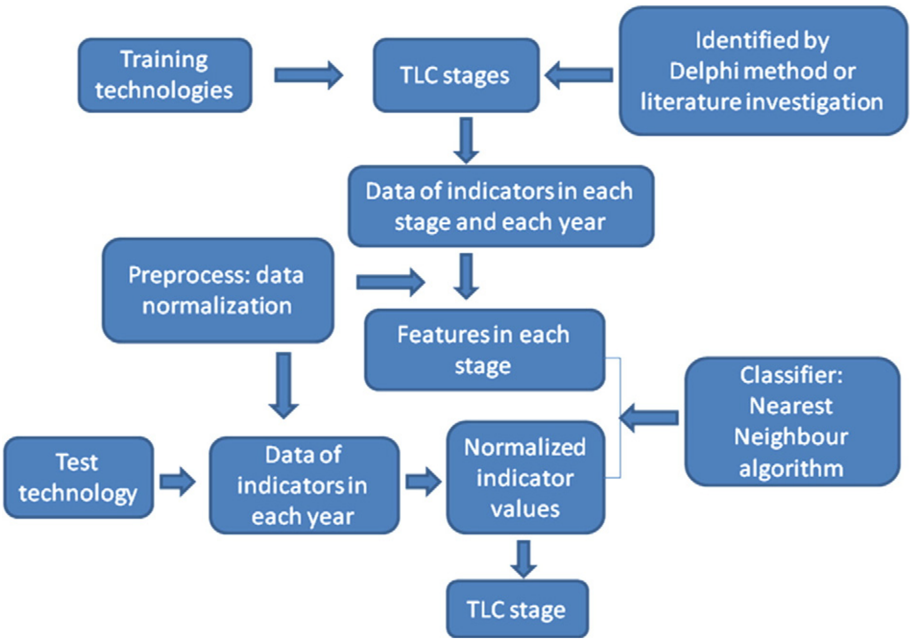

Fig. 2. Framework of TLC analysis.

Table 2
Technology life cycle indicators.

No.	Indicator	Indicator description
1	Application	Number of patents in DII by application year
2	Priority	Number of patents in DII by priority year
3	Corporate	Number of corporates in DII by priority year
4	Non-corporate	Number of non-corporates in DII by priority year
5	Inventor	Number of inventors in DII by priority year
6	Literature citation	Number of backward citations to literatures in DII by priority year
7	Patent citation	Number of backward citations to patents in DII by priority year
8	IPC	Number of IPCs (4-digit) in DII by priority year
9	IPC top 5	Number of patents of top 5 IPCs in DII by priority year
10	IPC top 10	Number of patents of top 10 IPCs in DII by priority year
11	MC	Number of Manual Codes (MCs) in DII by priority year
12	MC top 5	Number of patents of top 5 MCs in DII by priority year
13	MC top 10	Number of patents of top 10 MCs in DII by priority year

in DII by application year for the Application indicator and count the number of patents in DII by priority year for the Priority indicator.

2.1.2. Assignee

Some business software, such as PatentEX and Webpat, has adopted assignee numbers to develop an S-curve. Three types of assignees are provided in DII: corporate, non-corporate, and individual. Non-corporate assignees include universities, academies, non-profit labs, and centres. Because of the difference in patent law between the U.S. and other countries, too many individual assignees are observable in U.S. patents, and some of them are inventors. Therefore, we only consider the corporate and non-corporate assignees. We count the respective numbers for each of these two indicators in DII by priority year.

2.1.3. Inventor

This indicator indicates the amount of human resources invested in R&D of one particular technology. Number of Inventors has been used as indicator to measure the TLC of RFID [21]. We count the number of unique individual inventors of each year by priority year.

2.1.4. Citation

Two major types of cited references are given in a patent: science literature [22,23] and other patents [24]. Backward citations to science literature indicate a linkage between science and the patented technology. Backward citations to other patents may indicate a linkage between other technologies and the patented technology. The number of these two kinds of references can be found on the front page of the patent documents. We count the number of literature citations and the number of patent citations in DII by priority year.

2.1.5. IPC (four-digit)

The International Patent Classification (IPC) system, established by the Strasbourg Agreement 1971, is the most widely used hierarchical classification system of patents based on the different areas of technologies to which they pertain. It utilizes a language-independent symbol for the classification, adopted to varying degrees by every country or organization with an official patent office. Lerner [25] introduced four-digit IPC codes to measure the scope of each patent. So in this research, we consider the 4-digit IPCs and investigate three types of IPCs. The number of IPC codes represents how many fields are involved in the development of a technology. The IPC top 5 is a group of five IPCs with the highest number of applications. The IPC top 10 is another group of 10 IPCs with the highest number of applications. Generally, the top 5 or top 10 IPCs represent the main technology subjects.

IPC code has been used as an indicator to measure the technology life cycle [26]. We count the number of IPCs (4-digit) in DII by priority year for the IPC indicator; count the number of patents among the top 5 IPCs in DII by priority year for the IPC top 5 indicator; and count the number of patents among the top 10 IPCs in DII by priority year for the IPC top 10 indicator.

2.1.6. MCs

The Derwent manual code (MC) system is a hierarchical classification system developed by Derwent. It is similar to the IPC classification system. Whereas the IPC is assigned by the examining patent offices, MC is assigned by teams of subject experts at Derwent. The technology structure is also different: MC and IPC are complementary codes, used in this paper to measure technology subjects. We count the number of MCs in DII by priority year for the MC indicator; count the number of patents among the top 5 MCs in DII by priority year for the MC top 5 indicator; and count the number of patents among the top 10 MCs in DII by priority year for the MC top 10 indicator.

2.2. TLC stages of CRT and TFT-LCD

It is better to choose a training technology with four TLC stages. From the literature, we find that the Cathode Ray Tube (CRT) has been developed for more than 100 years and is now in the decline stage [27,28]. But the patent information in the early years is unavailable (patent data in DII covers 1963 to the present). So we choose another similar technology, the Thin Film Transistor Liquid Crystal Display (TFT-LCD), as the second training technology. Nano-biosensor (NBS) is chosen as the test technology.

We then focus on CRT and TFT-LCD technologies and assess their life cycle stages. We developed the questionnaires based on the concept of TLC given by Arthur D. Little [9]. Ten experts in CRT, TFT-LCD or display fields were asked to give the time periods of four stages for TFT-LCD and CRT. We obtained four responses. By discussing with two of the experts who gave similar time periods for CRT, we finally determined the TLC stages of CRT and the stages of TFT-LCD based on one related paper [29]. Table 3 shows the TLC stages of CRT and TFT-LCD as given by the experts and literature.

2.3. Search query

The search terms for each technology are defined simply but appear to capture the most relevant patents.

For TFT-LCD, the search terms are "thin film transistor* liquid crystal display*" in all fields. Using abbreviations "TFT" and "LCD" brings up many irrelevant records. So we add the IPC code, G02F1/13 (based on liquid crystals to control the intensity, phase, polarisation, or colour), for searching. In this way, we obtain 12,596 records for TFT-LCD.

Correspondingly, for CRT, as no IPC code exists, we use a Derwent Class Code (DC), V05 (Valves, Discharge Tubes and CRTs). So the search terms are "cathode ray tube*," CRT, or V05. In this manner, we obtain 34,469 records for CRT.

We divide NBS technology into two parts: one is a nano-related technology and the other is a biosensor-related technology. A query strategy for nanotechnology has been developed by TPAC at the Georgia Institute of Technology [30]. We refine our search terms for biosensors based on our earlier research [31] and add some keywords related to functions of biosensors, including "test" (or similar keywords, such as measure*, monitor*) and "nucleic acid*" (or some other bio-related keywords, such as lactate or cholesterol), and "sensor*." After combining the nanotechnology search query with the biosensor terms, we obtain 1493 records for NBS.

All the records are downloaded from DII, and VantagePoint software [www.theVantagePoint.com] is employed to extract, clean, and analyse indicator data.

2.4. Data process

First, we develop a map for 13 indicators of each training technology. Numbers of inventors suggest very interesting changes in different stages. Fig. 3, which presents the emerging and growth stages, shows that the number of inventors is typically higher than that of all other indicators. This declines in the mid-maturity stage (Fig. 4), but slightly increases in the following years. The number of inventors is less than some other indicators, such as application numbers and priority application numbers in the maturity and decline stages.

Trends of other indicators also show different patterns. In the emerging and growth stages, indicators 1, 2, 4, 5, 9, 10, 11, 12, and 13 show similar trends; indicator 6 and 8 look similar; indicators 3 and 7 are different from the others and also different from each other. In the maturity and decline stages, indicators 1, 2, 9 and 10 are similar. To make clear which indicators are similar with the others in the development trends, we employ a cross-correlation analysis to measure the similarity among the 13 indicators in the four stages. Table 4 provides the results of the cross-correlation analysis ($r \geq 0.9$).

- Emerging stage: In group 1, indicators 1, 2, 3, 7, 9, 10, 11, 12, and 13 have strong correlations. Indicators 5, 6, and 7 are another group with strong correlations. Indicators 4 and 8 are uncorrelated.
- Growth stage: 11 of the 13 indicators are strongly correlated. Indicators 6 and 7 form the other group with strong correlations.
- Maturity stage: There are 5 groups in this stage. Indicators 1, 2, 3, 7, 8, 9, 10, 11, and 13 have strong correlations. Indicators 11, 12, and 13 form another group. Indicators 4, 5, and 6 are uncorrelated.
- Decline stage: There are 6 groups in this stage. Because CRT is still in its decline stage, the indicator performance should be interpreted with great caution.

Since the indicators show different trends in different stages, it might be better to combine all 13 indicators to measure the change of technology rather than using one single indicator.

It is common to process multidimensional data by matrix. The original data are extracted by VantagePoint and imported into MS Excel — 13 rows of indicators, 30 columns (years) for TFT-LCD (from 1978 to 2007), 36 columns (years) for CRT (from 1972 to 2008), and 24 columns (years) for NBS (from 1985 to 2008).

Table 3
TLC stages of CRT and TFT-LCD.

Stage	Emerging	Growth	Maturity	Decline
Period (year)(CRT)	1897–1929	1930–1972	1973–2000	2001–2020
Period (year)(TFT-LCD)	1976–1990	1991–2007	2008–	–

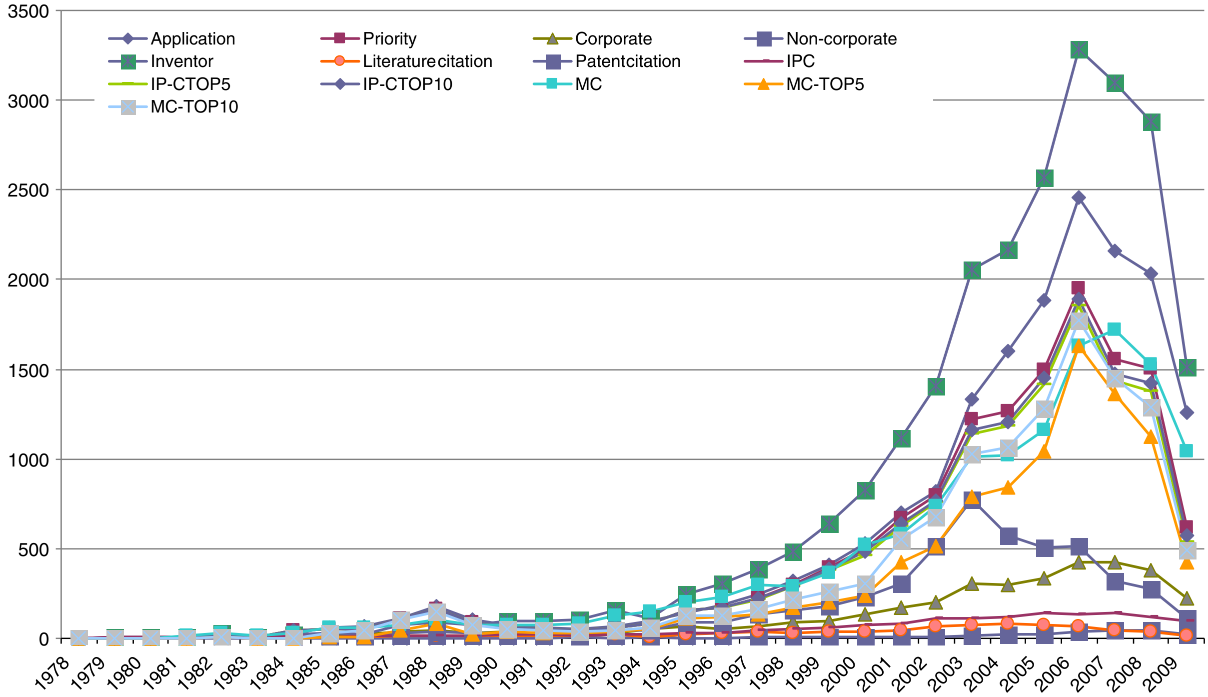

Fig. 3. Development trends of 13 indicators (TFT-LCD).

We propose a normalisation method with two steps to pre-process the original data. The first step is data smoothing by calculating three-year moving averages. The original data are defined as

$$A = [A_1, A_2]. \tag{1}$$

Here A_1, A_2 represent the original data of TFT-LCD and CRT respectively. Then the smoothed data of TFT-LCD and CRT are defined as

$$\overline{A} = \left[\overline{A_1}\ ,\overline{A_2}\right] \tag{2}$$

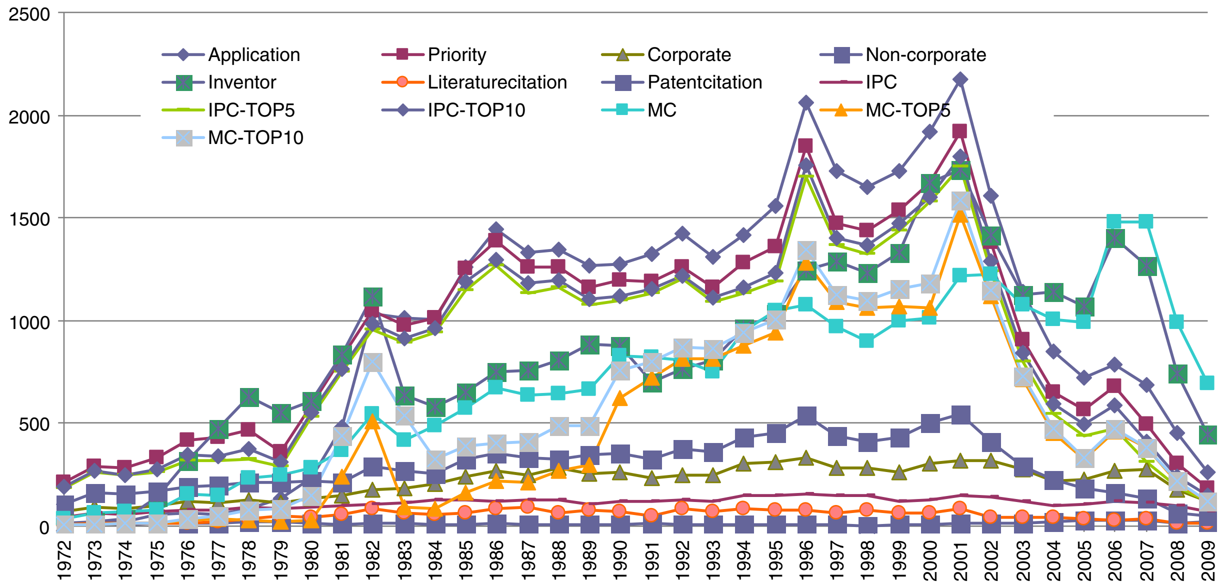

Fig. 4. Development trends of 13 indicators (CRT).

Table 4
Cross-correlation analysis for 13 indicators (r ≥ 0.9).

TLC stage	Emerging	Growth	Maturity	Decline
Group 1	1, 2, 3, 7, 9, 10, 11, 12, 13	1, 2, 3, 4, 5, 8, 9, 10, 11, 12, 13	1, 2, 3, 7, 8, 9, 10, 11, 13	1, 2, 7, 9, 10, 12, 13
Group 2	5, 6, 7	6, 7	4	2, 3, 8
Group 3	4		5	4
Group 4	8		6	5
Group 5			11, 12, 13	6, 7
Group 6				11

$$\overline{A}_1(i,j) = \frac{A_1(i,j+1) + A_1(i,j) + A_1(i,j-1)}{3}, i\in[1,13], j\in[2,29] \tag{3}$$

$$\overline{A}_2(i,j) = \frac{A_2(i,j+1) + A_2(i,j) + A_2(i,j-1)}{3}, i\in[1,13], j\in[2,35]. \tag{4}$$

$\overline{A_1}, \overline{A_2}$ represent the smoothed data of TFT-LCD and CRT respectively.

The next step is to divide the smoothed data by their maximums. The normalised data are defined as

$$\hat{A} = \left[\hat{A}_1, \hat{A}_2\right] \tag{5}$$

$$\hat{A}_1(i,j) = \frac{\overline{A_1}(i,j)}{\max_j \overline{A_1}(i,j)}, i\in[1,13], j\in[1,30] \tag{6}$$

$$\hat{A}_2(i,j) = \frac{\overline{A_2}(i,j)}{\max_{j'} \overline{A_2}(i,j)}, i\in[1,13], j\in[1,36] \tag{7}$$

$\hat{A}_1, \hat{A}_2$ represent the normalised data of TFT-LCD and CRT respectively.

We then apply the same normalisation steps to the NBS data. The smoothed data and the final normalised data of NBS are defined as $\overline{B}$, $\hat{B}$ respectively,

$$\overline{B}(i,k) = \frac{B(i,k+1) + B(i,k) + B(i,k-1)}{3}, i, \in[1,13], k\in[2,23] \tag{8}$$

$$\hat{B}(i,k) = \frac{\overline{B}(i,k)}{\max_k \overline{B}(i,k)}, i\in[1,13], k\in[1,24]. \tag{9}$$

Then the nearest neighbour (NN) classifier is applied to the normalised data to measure the stage status of NBS. NN is widely used in pattern recognition, machine learning, and computer vision. It has been shown that NN has consistently high performance. It involves a training set and a test set. The test points in the test set are classified by calculating the distance to the nearest training point in the training set; the sign of each point then determines the classification of the test sample. In the paper, we employ it to process the multi-dimensional (13-D) data.

The normalised data of TFT-LCD and CRT form the training set Ω ($\Omega \subset R^{13}$), and the normalised data of NBS are considered as a test set Ψ ($\Psi \subset R^{13}$). There are 30 training points in the TFT-LCD training set, 36 training points in the CRT training set, and 24 test points in the NBS test set. The training points a_j and test points b_k are defined as

$$a_j = \begin{vmatrix} \hat{A}(1,j) \\ \vdots \\ \hat{A}(13,j) \end{vmatrix}, \tag{10}$$

$$b_k = \begin{vmatrix} \hat{B}(1,k) \\ \vdots \\ \hat{B}(13,k) \end{vmatrix}. \tag{11}$$

Since we have the TLC stages of TFL-LCD and CRT, we can form the label set of training set

$$L = \{l_a | l_a = 1,2,3,4, a\in\Omega\}, \tag{12}$$

l_i represents TLC stages of TFT-LCD and CRT.

For a training point $a_j \in \Omega$ and test point $b_k \in \Psi$, the distance between a_j and b_k is defined as

$$dist\left(a_{\mathrm{j}}, b_k\right) = ||a_j - b_k|| = \sqrt{\sum_{i=1}^{13} (a(i,j) - b(i,k))^2}. \tag{13}$$

For each test point $b_k \in \Psi$, we compute the distance between b_k and all the training points and find the nearest training point (Fig. 5), that means

$$dist\left(a_{j0} - b_k\right) = \min dist\left(a_j, b_k\right) \text{s.t.} a_j \in \Omega. \tag{14}$$

Then the label information of b_k is considered identical to that of a_{j0}, namely $l_{b_k} = l_{a_{j0}}$. In order to obtain all label information for NBS, we have to calculate the minimum distance between each test point and all the training points and then obtain all the label information of b_k, that is the TLC stage information of NBS.

3. Results and implications for management

Table 5 shows the label results for each test point of NBS. The label information of the first 12 test points (1985–1996) of NBS can be matched with that in the emerging stage of TFT-LCD, and the label information of the second 12 test points (1997–2008) of NBS can be matched with that in the growth stage of TFT-LCD.

We separately showed our results to two NBS experts who are working for Georgia Institute of Technology. In their opinion, the results fit their understanding for the development of NBS.

Therefore, NBS is still in its growth stage (1997 to the present). And according to the definition of TLC, in a technology's growth stage, there are pacing technologies with high competitive impact that have not yet been integrated into new products or processes. That means, some product-related technologies may be commercialised in the future; however, at the moment, these technologies need more work in order to resolve key problems. The most successful commercial biosensor technology—surface plasmon resonance—does not have a very good limit of detection (LOD), the nanoparticle based SPR (or local SPR) can provide excellent LOD. However, the current fabrication technology is expensive [32]. Therefore, the fabrication technology is one of the pacing technologies of NBS. In this stage, a lot of challenging problems must be overcome, such as enhancement of gene array and protein array, and some new and promising technologies are still under research [33].

Technology observers can make their R&D investment decision by using the proposed approach. The result shows that NBS is in a growth stage. It means that there are many technologies still in development, including SPR. Technology managers might inform their NBS R&D investments by analysing patent application data from 1997 to the present to identify hot research topics or technological gaps. For some NBS related companies that have enough money for R&D, it is a good time to invest in NBS to pursue potential markets.

4. Conclusions

How might technology life cycle analysis based on patents contribute to FTA? This approach to gauge a technology's growth trend provides a more robust projection. However, as mentioned in Section 1, extrapolative technology trend approaches are not

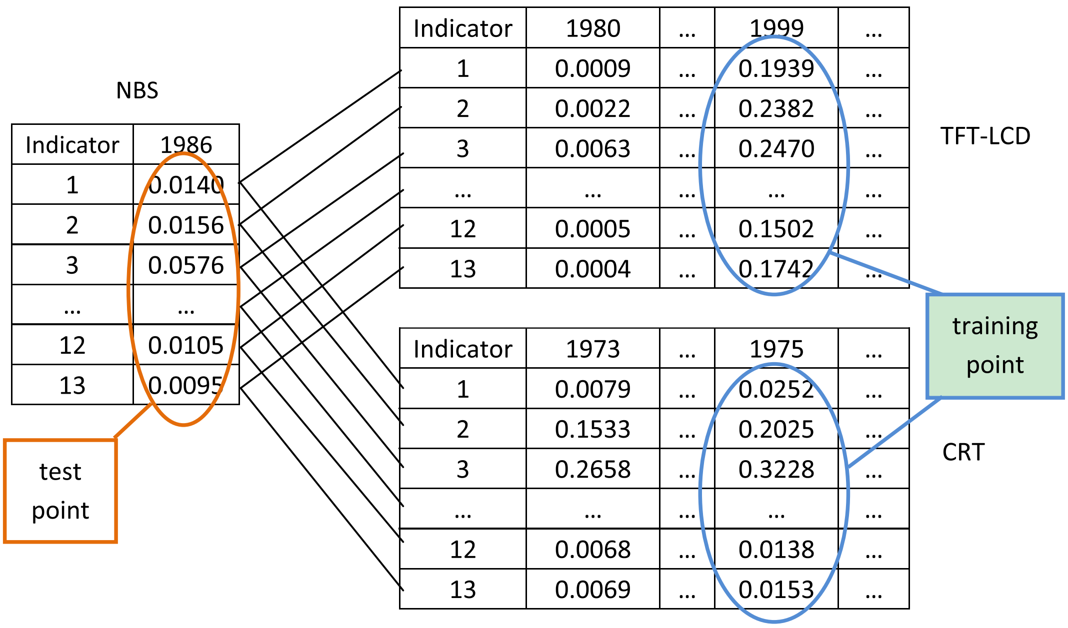

Fig. 5. An example for computing the distance between test point and training points.

Table 5
TLC stages of NBS.

	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
l_b	1	1	1	1	1	1	1	1	1	1	1	1
	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
l_b	2	2	2	2	2	2	2	2	2	2	2	2

So the TLC stages estimated for NBS are:
Emerging stage ($l_b = 1$): 1985–1996.
Growth stage ($l_b = 2$): 1997–present.

definitive projections. Indeed, explicit analyses of what factors and forces are apt to alter projected developmental trends are worthwhile — note Ted Gordon's "Trend Impact Analysis" (TIA) especially [34]. A thoughtful anonymous reviewer reminded us of the wide range of factors that could change a development trajectory, including new combinations of technologies (existing and/or emerging), and many socio-economic forces (e.g., fluctuations in demand, regulations, ethical or environmental concerns). In addition, one would want to address the potential "unintended, indirect, or delayed" impacts on society of introducing new technologies – i.e., technology assessment – but that is beyond the scope of this study.

This study is based on patent documents; it adopts 13 indicators that can be quantified to measure the TLC stages of an object technology. We introduce the nearest neighbour classifier, which is commonly used in pattern recognition and some other fields, to process the 13-D data by calculating the nearest distance among the test point and training points to find the most similar feature in training points. Therefore, the stage of the training point with the nearest distance to the test point predicts the stage of the test point. In this study, we take TFT-LCD and CRT as the training technologies and NBS as the test technology. The result shows that NBS is still in its growth stage. This means that there are pacing technologies with high competitive impact that have not yet been integrated into new products or processes. Companies with strong capital strength and technical capabilities should participate in this stage and develop differentiated products to capture the market [35]. This method can be used not only in NBS but also in other technology fields, since data of the all indicators can be downloaded from most patent databases.

Certainly, our study possesses limitations. First, only two technologies serve as the training technologies to calculate the similarity feature with the object technology (test technology). This is due to the lack of ideal training technologies with four TLC stages. So, this study resembles a laboratory test. Though the results seem reasonable, we still need to find more technologies and obtain more data to validate the method. Second, we did not consider the technology type. TFT-LCD and CRT are categorised as single-technology type, but NBS is a multi-technology: it involves nanotechnology and biotechnology, with diverse application possibilities. Different types of technologies may have different developing patterns, especially for those technologies close to basic science, such as biotechnology. Future research should also take this into account. Third, the classifier we used in this paper is the nearest neighbour classifier. For future study, we will test some other classifiers, such as nearest feature line (NFL) and Bayesian classifier, to assess if we can improve indicator performance.

Many papers have pointed to the desirability of improving the accuracy of trend projection methods [36–39]. If TF is to aid in decision making, robustness is vital. How might this TLC estimation method fit in with other FTA techniques? Porter [40] suggested considering the use of multiple FTA methods tailored to the type of foresight study. He distinguishes 13 method families. TLC is intriguing in that it combines aspects of several of those: trend analyses (where it best fits), but also monitoring and intelligence, matrices (analogies), modelling, and a hint of roadmapping. More importantly, we suggest that TLC would be complemented by informal and/or formal expert opinion to check the results and to identify factors apt to alter the course of development that TLC suggests. It is oriented mid-term (i.e., 2–10 years in the future) to provide a more robust sense of likely developmental trajectory than does single variable trend projection.

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