Research and development progress assessment through technological and scientific intelligence

Tugrul U. Daim*

Department of Engineering and Technology Management,
Portland State University,
Portland, OR 97201, USA
E-mail: tugrul@etm.pdx.edu
*Corresponding author

Nathasit Gerdsri

College of Management,
Mahidol University,
Bangkok, 10400, Thailand
E-mail: nathasitg@hotmail.com

Abtsract: It is critical for Research and Development (R&D)-driven organisations to have access to intelligence on the progress of the research in universities and public or private laboratories as well as on the status of their competitors. This paper introduces three concepts: time lag between different scientific indicators, visual correlation between scientific indicators and actual technology performance and finally an activity metric for assessment of competition between an existing and an emerging technology. The results indicate that the introduced concepts, which are based on the bibliometric and patent analysis approaches, allow researchers to generate intelligence on emerging technologies and innovations supported by the wealth of today's public electronic information database.

Keywords: R&D management; technology management; technology forecasting; bibliometrics; patent analysis; interconnect technologies.

Reference to this paper should be made as follows: Daim, T.U. and Gerdsri, N. (2009) 'Research and development progress assessment through technological and scientific intelligence', *Int. J. Technology Intelligence and Planning*, Vol. 5, No. 4, pp.341–356.

Biographical notes: Tugrul U. Daim is an Associate Professor of Engineering and Technology Management at Portland State University. Prior to his academic career, he had worked at Intel Corporation. He received his BS in Mechanical Engineering from Bogazici University in Turkey, MS in Mechanical Engineering from Lehigh University in Pennsylvania, another MS in Engineering Management from Portland State University and a PhD in Systems Science-Engineering Management from Portland State University. He has published more than 70 papers in peer reviewed journals. He is currently an Editor-in-Chief for *Int. J. Innovation and Technology Management*.

Nathasit Gerdsri, PhD, is a Full-Time Faculty at the College of Management, Mahidol University (Thailand). Currently, his TRM research is focused on how to operationalise technology roadmapping process. His research activities are carried out through academic and consulting projects. He received PhD from the Department of Engineering and Technology Management, Portland State University. A part of his dissertation on the Development of Technology Development Envelope (TDE) for roadmapping of emerging technologies was nominated to receive the outstanding paper award at PICMET in 2005. Prior to these, he worked for Intel's R&D lab in Hillsboro, Oregon.

1 Introduction

As the time to market decreases in industries, intelligence on Research and Development (R&D) becomes strategically important. This paper explores emerging approaches using the application of bibliometric analysis on publication and patent databases to acquire such intelligence through a case study. These two databases have been well accepted that their data can be synthesised to fill the gap of information deficit on determining the development progress of emerging knowledge, practices and technology applications. The results of this study show that the synthesised information of conference and journal publications can be used as an early warning signal indicating the birth of emerging activities. The activities in conference and journal publications seem to take place in 2–3 and 1–2 years, respectively, ahead of the patenting activities. This observation seems to be true for emerging knowledge and practices but not for emerging technology applications. From our preliminary analysis, we think that this discrepancy could come from the difference in the process of naming the title of emerging knowledge, practices and technology applications. Since the publication activities of emerging technology applications would not start until developers reveal the titles of their technology applications in public domains and these steps are generally done after developers file patent protecting their intellectual properties. The time lags identified in this case study may not hold for other fields. So, it is critical to understand the relationships in different industries. To predict the development progress of emerging knowledge, practices and technology applications, the traditional forecasting methods are not applicable because of the limited historical information of any emerging technology. The bibliometric analysis is one of the few approaches capable to fill the gaps of missing information by synthesising on publication information in public electronic databases. Although there are several limitations in this study, its contribution leads to the development of further propositions for future research. The major research questions and propositions derived through this paper include the need for cultivating technological and scientific intelligence and the emergence of using scientific indicators in newer ways than ever used before so that they can provide the intelligence sought.

2 Literature review

Today's R&D-driven companies need to pay attention to technological and scientific intelligence to stay competitive. However, neither the need nor the research aiming at providing such intelligence is new. Lichtenthaler (2004, 2007) analysed the technology intelligence processes in 25 multinational companies in the pharmaceutical, telecommunications equipment and automobile industries in the context of radical technological change and identified three types of organising technology intelligence: the participatory, the hybrid and the hierarchical technology intelligence process. Kerr et al. (2006) provided a framework that would integrate technology intelligence into technology planning process. Early studies providing direction include de la Mothe (1992) and his review of the Frascati Manual provided by OECD as a report on science and innovation statistics. There is a significant amount of research published in the area of predicting consumer behaviour with regard to technologies. Bass curve is one of the most known approaches to predict the diffusion of new products (Bass, 1969). Rogers (1962) also provided leadership in understanding the elements of diffusion for new innovations. Davis (1986) introduced the Technology Acceptance Model providing further understanding of the elements that made us adopt new technological innovations. A large amount of research focused on different parts of the ideas introduced by these leaders. For example, a group explored the effect of hype, which impacts the early diffusion of new innovations. It is seen later that this type of hype impacted later diffusion in a negative way (Yeon et al., 2006). Overall, these early studies and those followed them are based on behavioural models. Another group of research titled Technological Forecasting started to develop methods that have been used in bio and physical sciences. Growth curves, for example, are based on prey and predator relationships and depict technology substitution very well. Simulation, scenarios, analogies and Delphi panels are other approaches used extensively by this group of researchers (Martino, 1983). However, all of these methods are dependent on historical data, which emerging technologies lack. So, other methods of acquiring such intelligence are required. Emergence of online databases with the diffusion of internet has enabled researchers to develop another growing research field aiming at providing the required technology intelligence. There are key leaders who have been providing direction on research. Porter and Detampel (1995) provided how to generate effective intelligence on emerging technologies through monitoring and bibliometrics. Watts and Porter (1997) build upon this and present an array of bibliometric measures for forecasting technologies. This provides a good means to combine technological trends, mapping of technological interdependencies, and competitive intelligence to produce a viable forecast. Their study illustrates by assessing prospects for ceramic engine technologies. Porter (2005) and Porter and Cunningham (2004) took this to another level with an approach taking advantage of science and technology publication and patent abstract databases and developing templates of innovation indicators to answer questions. Alencar et al. (2007) related patent trends to product life cycles confirming further that performance can also be related. Jaffe and Trajtenberg (2002) demonstrated the use of patents and citations data for research on the economics of innovation. They provided direction for the researchers in the field by laying out the conceptual foundations for a range of applications, such as examining the geographic pattern of knowledge spillovers and evaluating the impact of university and government patenting. Use of patent data have been explored frequently in recent years. González-Álvarez and Nieto-Antolín (2007), lo Storto (2006), Saiki et al. (2006) and Buesa et al. (2006) explored use of patent data to understand innovation better. Llor (2007) investigated the reasons behind the delay between patenting and technology transfer. Another leading researcher is Ronald Kostoff. Kostoff (1994, 1995) first introduced the use of bibliometrics as a measure assessing research impact. He then expanded the measure as a scanning tool identifying innovation opportunities (1999). Kostoff et al. (2001) labelled the approach as Database Tomography (DT). They described as a

> "textual database analysis system consisting of two major components: (1) algorithms for extracting multiword phrase frequencies and phrase proximities (physical closeness of the multiword technical phrases) from any type of large textual database, to augment (2) interpretative capabilities of the expert human analyst. DT has been used to derive technical intelligence from a variety of textual database sources, most recently the published technical literature as exemplified by the Science Citation Index (SCI) and the Engineering Compendex (EC)."

Later on, several applications of his approach were used in differing areas. Kostoff et al. (2002) applied DT on electrochemical power applications. Kostoff et al. (2005) applied it on power sources generating roadmaps. Kostoff et al. (2005) applied it on a country and provided insight into Mexico's science and technology infrastructure. Recent studies build upon the base created by these early researches and expanded into gaining intelligence in global trends, countries, regions, organisations or individual scientists. Falagas et al. (2006) used bibliometric analysis to chart out global trends of research productivity in tropical medicine, Acta Tropica. Hicks et al. (2001) used patent analysis to highlight the composition of innovative activity in the USA. Shapira and Youtie (2006) provide the cases from the southern US states where data mining was used to inform the economic developers. Butler (2003) investigated increase in publication counts in Australia and attempted to link it to increased funding. Butcher and Jeffrey (2005) used bibliometric analysis this time to identify collaborations between industry and the academic institutes. Levitas et al. (2006) utilised US patents issued to Integrated Circuit (IC) manufacturers from 1975 to 1994 to analyse a firm's decision to pursue a technology across varying levels of technological turbulence. Meyer (2006) investigated this time those who are applying for patents and explored if they were better than those that are just publishing papers. We also see a rise in research improving the methodologies. Daim et al. (2006) integrated bibliometric analysis with other forecasting methods to improve the accuracy of the forecasts. Morris et al. (2002) introduced Database Information Visualisation and Analysis system (DIVA), which is a computer programme that helps perform bibliometric analysis of collections of scientific literature and patents for technology forecasting. von Wartburg et al. (2005) used multi-stage patent citation analysis to explain aspects of technological change. Park et al. (2005) and Yoon and Park (2004, 2005) expanded the field by providing additional intelligence to the analyses introduced by early research. Sun et al. (2007), Choi et al. (2007), Hu and Tseng (2007), and Bengisu and Nekhili (2006) provided additional approaches and cases in using patent trends for acquiring technology intelligence. The field of using scientific indicators may be getting a label already. A recent special issue published in Technology Forecasting and Social Change was titled "Literature-Related Discovery (LRD)". Lead by Kostoff (2008a, 2008b) and contributions by Kostoff et al. (2008a, 2008b, 2008c, 2008d, 2008e) and Kostoff and Briggs (2008), explored new applications ranging from diseases to environmental issues. Another special issue targeted China and India and used this approach to assess scientific progress levels (Kostoff et al., 2007a, 2007b, 2007c, 2007d, 2007e).

So, the field has been growing at an exponential rate. Methodologies extracting and analysing scientific indicators have gone very sophisticated. However, there are still major gaps. The first one is the methodologies are still developed with more scientific input rather than practitioner input. Second, there is less emphasis on developing linkages to actual technology performance and thus use forecast of scientific indicators to forecast technological performance. Similarly, there is little works done in understanding the relationship among different scientific indicators. Especially, the existence of time lags among different indicators will enable us to develop forecasts as early indicators such as when conference presentations start appearing. And finally there is a need for developing single activity metrics that can be comprehended faster and better. Therefore, we expand our objectives through literature search as follows:

1 What kind of technological and scientific intelligence is required and useful for managers responsible for decision making in technology-oriented enterprises?

2 Are there any linkages among different types of scientific indicators?

3 Is there any linkage between scientific indicators and technological performance?

4 Are there any single metrics under which multiple scientific indicators can be compiled?

3 Methodology and results

This paper attempts at providing additional improvement opportunities in the methodologies in using bibliometrics and patent analysis for technology forecasting. We will accomplish this through use of case studies. Case study methodology is defined by Yin (1993). He provided several examples of use of case studies in research (Yin, 1994). We will explore the objectives outlined in the previous section through the case study analysis.

What kind of technological and scientific intelligence is required and useful for managers responsible for decision making in technology-oriented enterprises?

The case organisation reviewed in this paper had three major groups using technology intelligence:[1]

Research groups

These are generally working on projects that are more likely to get integrated to the product groups in another 5–7 years. They generally have employee base of several PhDs with key networks in the academia and the industry. They work with key professors/universities and rely on their current network to extend to new partnerships. They also use technical conferences and technical/trade journals to identify any emerging leaders. There are common mechanisms to be able to link to technology sources so that intelligence can be maintained. The most important one is university grants. All research-driven companies use this mechanism to acquire technologies as well as to acquire intelligence on other related technologies. It takes huge budgets ($100M annually) to be able to form and maintain such networks.

Product groups

Product groups have shorter timeline that they have to worry about, and they do not use scientific indicators. They rely more on industry/professions societies/groups and news that they receive from them. They have reported to develop their own intelligence tools at times. One of the companies developed a process to mine competitor's open positions for hire. Specifically, they were mining the skill sets sought and determining the features that their competitors were after. However, there will be an opportunity for use of this tool in 'technology development' groups. These groups do not belong to the research groups, however they act more like an agent between the product and research groups. Their interest would be on the patent analysis, which would help them to identify their industry counterparts.

Planning and marketing groups

Planning groups use professional services providing reports done through mining news, patents and publications. These groups are responsible for putting together the product plans for the next 5–8 years. And, the critical data they need include feature sets and performance targets. Marketing groups also seek intelligence mostly on competitors' activities. They use similar services for this as well. Overall, this group is interested in specific data and does not care where it comes from. That is why they do not necessarily think that citation analysis and patent analysis will provide them the data they need. Table 1 summarises the needs identified through the case study. The need for intelligence on performance and alternative/available technologies is repeated by many groups. So, linking analysis of scientific indicators to the performance is appropriate.

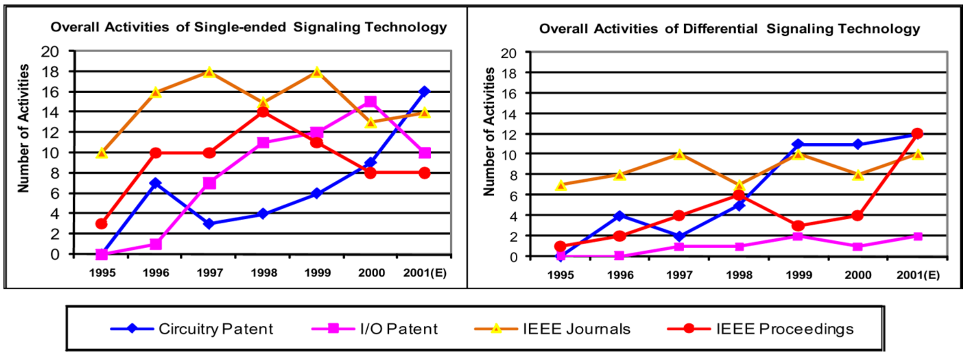
Table 1 Technology intelligence needs

	Tasks	*Intelligence required*
Research groups	Emerging technology assessment	Alternative technologies and performance targets
	Technology foresight	Technology parameter forecasts
	Emerging technology transfer – identifying the technologies to transfer into the company or country	Info on sources and actors – such as available or upcoming technologies and their origins
Product groups	Technology target spec	Performance forecast
	Technology evaluation and selection	Available technologies
	Technology acquisition	Technology owners and their background
	Technology roadmapping	Mapping out all the key information
	Technology transfer	Info on all sources and actors
Marketing and planning groups	Product feature sets	Network diagrams of the industry or sub industry
	Feature performance targets	Performance forecast
	Adoption rates	Diffusion curves
	Competitor intelligence	Potential plans of the competitor
	Industry intelligence	Movements in the industry
Human resources	Hiring strategic skill sets	Universities professors
	Competitor hiring intelligence	Hiring data of the competitor
Venture Capital	Start up funding	Investment risks
	Research funding	Disruptive technology developers

Are there any linkages among different types of scientific indicators?

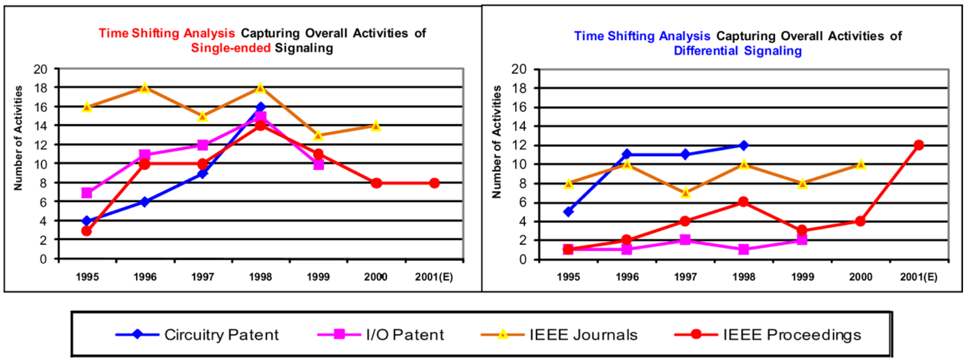
One of the difficult decisions that managers in R&D-driven organisations have to make is to pick a technology over another one. This becomes even more challenging in the case of emerging technologies where their past performance parameters do not exist. The process included use of experts and mining scientific and patent databases. For demonstration of the methodology, two competing interconnect technologies were picked: Single-ended vs. Differential Signalling Technology. Single-ended signalling is a traditional method in routing signals whereas differential signalling is an emerging method for the same purpose practised by printed circuit board designers. The time frame was from 1995 to 2001. Current leading technology in this case is the single-ended signalling and the challenger is the differential signalling. Experts consulted for this analysis belonged to the organisation studied as a case. These people are technical experts. Their initial task was to provide us a list of different keywords. We used four or five technical synonyms of single-ended and differential signalling. Searching domains were US Patent Database and IEEE Electronic Library. Two patent classes were recommended by technical experts: Class 710/126: Electrical Computers and Digital Data Processing Systems: Input/Output; Class 326/86: Electronic Digital Logic Circuitry. The following sections will describe the methodology and results achieved in every step. The analysis was initiated with patent analyses. The keyword search yielded several patents in each patent class. The experts reviewed and eliminated some of the patents, as they were not related to the technologies under evaluation. Patent activities from two different patent classes were charted and extrapolated using polynomial extrapolation over time as seen in Figure 1. One of the patent classes showed differential signalling as an emerging one. In the other class it was not clear if it was gaining ground yet. Although a polynomial extrapolation was indicating that differential signalling would catch up in 2–3 years, several other types of extrapolation formulas would show otherwise. Not relying on a single metric is critical as seen in this case Figure 1 shows a very competitive race between two alternative technologies. Next step was to search for the same keywords in IEEE conferences and journals. After reviewing the results with experts, we graphed trends in journal publications and conference proceedings as seen in Figure 1.

Figure 1 Comparisons of all activities (see online version for colours)



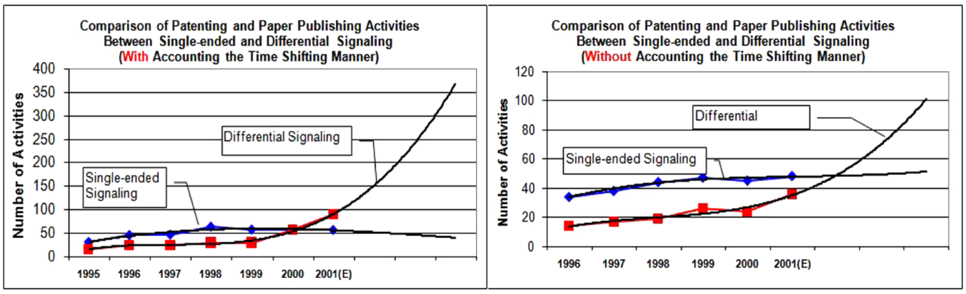
Both patent and journal analyses indicated that differential signalling was still behind single-ended signalling, however was catching up according to the extrapolations within 2–3 years. We did not need to do any extrapolation for conference papers as differential signalling had already caught up with single-ended signalling. Observing similar trends however different statuses in time is not unusual, as there is a time lag among the metrics we have been using. That is why we considered the time it takes for papers to be published and patents to be granted vs. conference presentations. We shifted journal papers by one year after reviewing the delta between submission and publication dates and I/O patents by 2 and Circuitry patents by three years after reviewing the delta between application and grant dates. Figure 2 shows the time lag insertion for both technologies. The time lag insertion showed a visible synergy among the metrics. All metrics were indicating a settling type of behaviour for single-ended signalling whereas metrics were showing an upward trend for differential signalling.

Figure 2 Comparison of all activities (after time lag insertion) (see online version for colours)



Integrating all patent and publication activities into a single metric can also provide the overall perspective indicating the momentum of emerging technologies. Figure 3 provides a clear visual showing that differential signalling is the winning technology.

Figure 3 Integrating all metrics (w and w/o time lag) (see online version for colours)

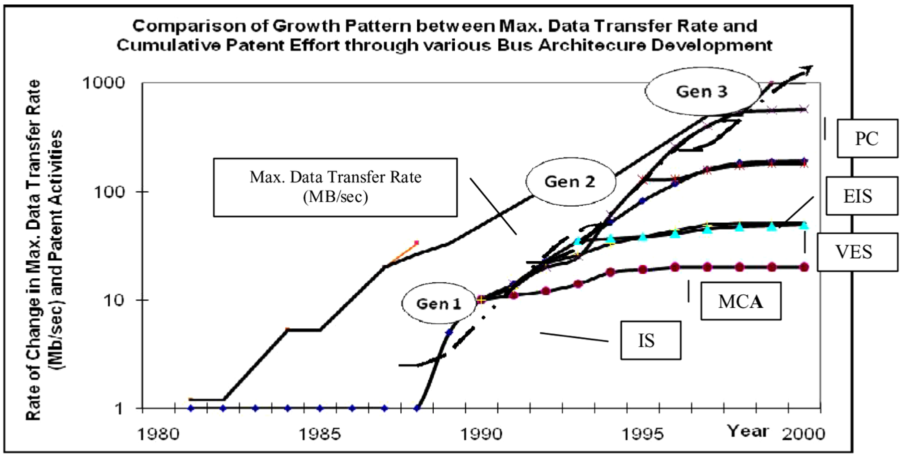


Is there any linkage between scientific indicators and technological performance?

Standards can also be a challenge for decision makers in the R&D-driven organisations. The R&D managers need to ensure that their product will be in compliance with majority of the standards in their fields and they need to ensure that they know about any new standards that may disrupt their business. To investigate this problem, we picked interconnect bus standards as a topic related to the first case investigated.

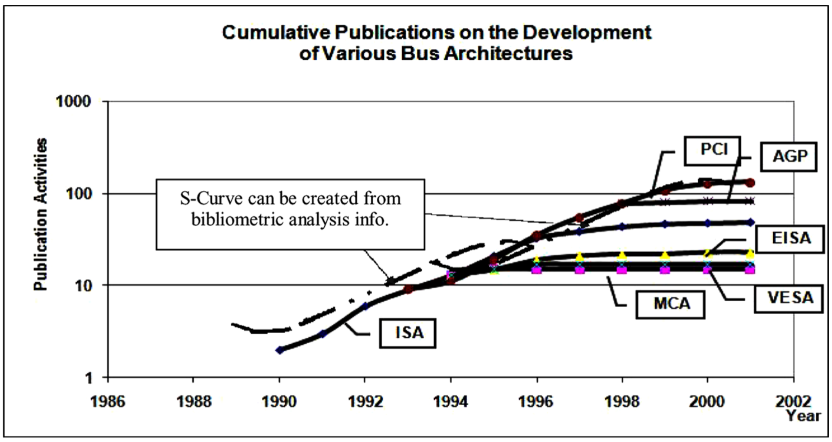
Standards define the limits of technological parameters so designers working on new printed circuit boards with advanced signalling technologies. The only difference is that this time we have past performance data that we can also use. Plotting and extrapolating the parameters "Clock Speed" and "Maximum Data Transfer Rate" let us observe the exponential rise of both parameters. Figure 4 presents performance and cumulative patent activity on the same graph. There is a visible similarity between the two graphs. When looked more carefully, we can even label three generations of interconnect standards: ISA, PCI and a third generation of interconnect standard, which at the time of this research was under development.

Figure 4 Technology performance mapped to patent activity (see online version for colours)



The next question is whether we can use publication trends in the same manner. Figure 5 shows the cumulative publication activity and we can identify standards replacing each other in this figure as well.

Figure 5 Publication activity trends (see online version for colours)



Through the analysis of second case, we were able to find some evidence indicating that the trend of patent and publication activity matches the trend of performance increase over time. Although further statistical analysis is required to confirm this, knowing that this possibility may exist provides researchers in this field with a research direction.

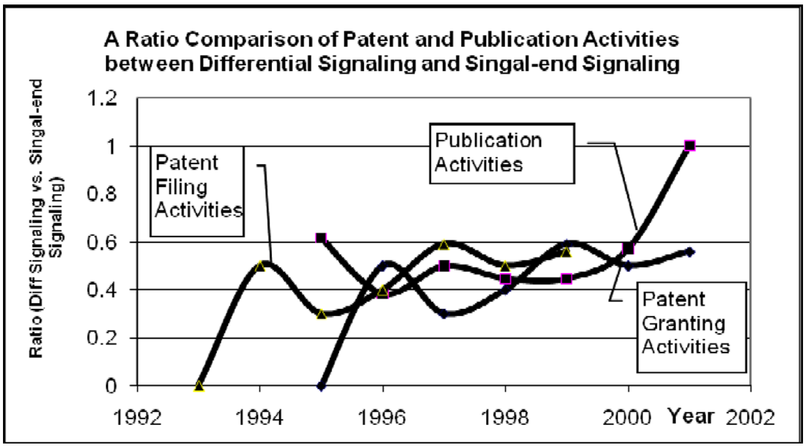
Are there any single metrics under which multiple scientific indicators can be compiled?

After reviewing two cases on the use of patent and publication to analyse the trend of emerging technologies, we can derive additional metrics to help us clarify the trends. One metric proposed as a result of this research is 'Activity Ratio' in which the number of activities (patents or publications) of an emerging technology divided by the same metric assessed for the existing technology. As this starts getting close to 1, it will be a good signal for us to pay attention to it.

Activity ratio = (Differential signalling)/(Single-ended signalling).

For demonstration purposes, patent and publication ratios for single-ended and differential signalling technologies are plotted. Figure 6 presents our results.

Figure 6 Activity ratios (see online version for colours)



There are several observations we can make from Figure 6. As previously mentioned, patent filing and granting data has a time lag. It may be a better idea to use filing data than granted data since filing data represent the actual time when the activities were started. Figure 6 shows that the trend of filing data is in phase with the publication trend and both trends indicate an upward direction towards the activity ratio of 1. Therefore, this analysis helps confirm that differential signalling will become a substitution technology over single-end signalling. However, there is still a concern that patent filing data may contain additional noise because not all patents filed would be granted.

4 Discussion

This section summarises the results of the case study analysis. The following were the initial research questions at the outset of this research.

1 What kind of technology intelligence is required and useful?
2 Are there any linkages among different types of scientific indicators?
3 Is there any linkage between scientific indicators and technological performance?
4 Are there any single metrics under which multiple scientific indicators can be compiled?

The answers we found for the first question were in contradiction with the consumer adoption literature. The targeted users of such methods were not interested in the prediction of the adoption, but on the future performance of technologies. However, they were more interested in specific analyses such as analysis of competing technologies or what technologies their competitors or leading researchers are working on. We have presented our results to a technology intelligence expert in another company and got his confirmation of our findings. Sophisticated mining of such information through the public databases will gain valuable time for the technology professionals.

Our limited visual analyses are indicating certain time lags among conference papers, journal papers and patents. Since our results are based on a very specific technology and an industry, we can expect that these will change in different applications and industries. However, using this approach and understanding the time lags in different fields would be useful. This finding presents a potential future research area. Defining the dynamics of such relationships is highly critical to those who are making decisions on technology investments. Such data would reduce the uncertainty and increase the quality of the decisions. Furthermore, the research can include the research awards and exploration of the time lag between those and the other indicators. Such research would help us to visualise technology roadmaps 5–10 years ahead.

Similarly, limited visual confirmation of similarities between publication or patent trends and technological performance requires further research and validation. Further results would help the targeted users immensely in charting out technological performance in the case of limited historical data. This result needs further exploration and is more likely to lead to comprehension of very useful relationships. Understanding such relationships would help us to evaluate emerging technologies better. In the case if such technologies, past performance data is missing, therefore using scientific and technological indicators can give us an idea on performance expectations.

Finally, we demonstrated limited use of single metrics for technology intelligence. Either combining all indicators into one or creating an activity indicator such as the one introduced earlier seem to be useful in exploring the case of competing technologies. Further exploration of these metrics in different fields will help validation. The proposed metric needs further validation through applications in different cases. Currently, it is an observation and cannot be validated with the available data. However, it is again a good indicator that may be used to summarise activity and report on competing technologies.

5 Conclusions, limitations and future research

Overall, this paper is presenting a methodology utilising patent and publication data with different approaches such as a time shift strategy to analyse competing technologies and standards. There is much more to be done as a future work after this study. Repeating it in many different areas and trying to establish links with actual performance data will help utilise patent and publication data to forecast emerging technologies, which generally lack historical performance data to do an accurate forecast.

Key conclusions of this study are:

- There are specific needs for technological and scientific intelligence in different organisations of R&D-driven companies. Many times such firms are working of developing products integrated with new technologies that the consumers may not have used before. Therefore, consumer adoption forecasts may not be viable in such cases. These firms would be more interested in reducing the uncertainty in the decisions they are making on technology investments. And, approaches discussed in this paper are promising to provide data to help with such improvement.
- There seem to be visual relationship among different scientific indicators. Comprehending such relationships would help us to reduce the uncertainty in the technology roadmaps developed thus helping the problem described in the first conclusion – reducing the uncertainty. Depicting the strategic position of the current technologies and emerging alternatives over the forecasted life-cycle pattern (S-curve) of each technology and providing an early warning signal of any coming technological change would help managers to strategically react and allocate human/financial resources as necessary.
- It is strategically very appropriate to integrate the metrics discussed in this paper, into evaluation processes of R&D-driven organisations. Today, many of the organisations rely on two types of data: one from their suppliers and the other from their networks. Those that can afford to maintain better and wider networks with access to university research through university grants and donations do have more advantage than those do not. However, accessing the data analysed in this paper will not need any additional huge funds, as it is available to public for free.
- The ability to identify emerging technologies and predict their performance trends through patent and publication data has several implications from a national perspective as well. Several developing countries aiming for the killer application would be able to use these tools to narrow their targets and utilise their resources more effectively. Similar analysis of technologies would be a very good input into any national foresight study.
- There are key technical findings as well. Patent information could likely be utilised to model technology replacements in addition to the upper limit information of technological performance parameters. Patent filing data information is more useful than granting data information, as it can provide an early warning signal. Bibliometric Analysis in publication activities could be used to supplement patent filing information.

As we conclude in this paper, we realised that several organisations had already started utilising these information sources: patent and publication. Anecdotal data indicates that companies are creating functions and titles responsible for mining this type of information. Also more and more consulting-type companies are starting to offer services doing exactly what was done in this paper. So, we believe that this field will support R&D organisations immensely and let them be more efficient within this decade by helping them make technology-related decisions more accurately.

The study has several limitations:

- Only one kind of application and industry is analysed. The relationships are expected to change in different industries. However, the approach used in this paper can be repeated and provide the dynamics of other industries as well.
- There are also technical limitations. Patent filing data was not available electronically until 2001. Observed linkages or relationships are all visual and therefore lack any mathematical backing. Further exploration of these using mathematical models will improve our understanding.
- There are limitations to use of this type of data as not all R&D activities are patented and only a fraction of R&D activities is published.
- There is not a long established theoretical history behind the approaches used in this paper as it is actually representing an emerging field that uses these types of indicators. Some authors call it 'Technology Mining' (Porter and Cunningham, 2004). We agree for example that we do not have enough data to validate the single metric concept at this point and therefore it is a weak proposition. Additional cases that will be based on our proposition will test this further.

There are several future paths through this paper.

1 The proposed approaches can be applied in different industries and on different technologies. Further data will improve our understanding of the dynamics and help us to reduce uncertainty in evaluating emerging technologies.

2 As this data is beginning to be available to use, we should also test the existing theories and target identifying relationships through that. For example, theory of hype cycle would be an excellent theory to test in a future paper. Our limited observations on Figure 6 may be explained by this theory.

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Note

[1]Part of the case which included patent analysis only was used later for evaluating the management capabilities of the case organisation by Daim and Hernandez (2008).