



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol.2, Special Issue 5, October 2014

A Review on Recent Developments in Technology Forecasting

Dr. R Sasikumar¹, Anisha Mohan²

Professor, Dept of Mechanical Engineering, Rajiv Gandhi Institute of Technology, Kottayam, Kerala, India¹

M Tech Industrial Engineering and Management, Rajiv Gandhi Institute of Technology, Kerala, India²

ABSTRACT: Technology forecasting (TF) is essential for responding to the emerging needs of private and public sector organizations in the highly competitive global environment. TF is an important research and development (R&D) policy issue for both companies and government. Vacant TF is one of the key technological planning methods for improving the competitive power of firms and governments. A number of models and techniques have been developed to deal with technology forecasting. In general, a forecasting process is facilitated subjectively based on the researcher's knowledge, resulting in unstable TF performance. This paper reflects the importance of technology forecasting, techniques employed for TF and recent developments in TF especially using patent analysis by investigating the various work carried out by different authors that progressed in this area.

KEYWORDS: Technology forecasting, methods, patent analysis

I. INTRODUCTION

Technology forecasting (TF) is used to predict the future state of a technology . TF can provide detailed and practical insights into future technology trends and thus can play an important role in research and development (R&D) management including strategy formulation. However, it is not easy to predict future technology trends because such forecasting efforts reflect both an art and science[8] . That is, forecast the future state of a particular technology requires scientific methods as well as domain knowledge. Previous studies have provided a few scientific methods such as those based on a quantitative analysis. However, TF models are typically based on qualitative methods such as Delphi.[9] Recently, some studies have proposed objective TF models. Most of these models employ patent documents as objective data, but they generally have some limitation as quantitative methods for objective TF.

TF is important to both companies and nations. Recently, economic competitiveness for both depends on technological prowess. Patents are a representative index of technological competitiveness because a patent document has diverse and detailed information about developed technologies[7]. Hence, patent analysis is an efficient emerging tool for TF especially for R&D planning and technology marketing..

II. OBJECTIVE OF THIS STUDY AND ORGANIZATION OF ARTICLES IN THIS PAPER

1. To understand the importance of technology forecasting in the current scenario of competitive global market.
2. To familiarize the development of technology forecasting over years.
3. To carry out a review of the existing technology forecasting methods and their application mainly using patent analysis.

This review tries to find the key elements of an efficient technology forecasting process along with the above mentioned objectives.

The organization of this paper is as follows:

First section provides an introduction to technology forecasting. The second section defines the objectives of the study. The methodology is shortly described thereafter. Importance and development of technology forecasting is



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol.2, Special Issue 5, October 2014

detailed in fourth section. Methods of technology forecasting is described in fifth section. A brief review about some of the conventional popular methods of technology forecasting is also given. Then in the sixth section, recent advances in technology forecasting is explained with the opinion of different authors.

III. METHODOLOGY

Diverse literature such as books and journal articles, searched via Emerald, Science Direct, has been used to gather the information to get the background information to achieve the goals of this paper. Several papers from the last years have been reviewed to know the state of the art of the existing and proposed methods of technology forecasting.

IV. TECHNOLOGY FORECASTING

A. IMPORTANCE OF TF

Our society is now completely reliant on technology—to drive the economy, to maintain and improve standards of living, and to protect Earth against the pressures of population and urban living. Nations are irretrievably enmeshed in a global economy fueled by innovation and competition. Therefore, technology is an increasingly important and challenging target for analyses to aid decision makers.

Technological developments are increasingly drawn directly from scientific research. This implies a need for tools to address less than orderly change processes. “Science forecasting” is called for to support and serve technology foresight. Social and political conditions appear to favor the emergence of TF. New, socially transforming technologies, such as genetic engineering, are widely perceived as risky or ethically questionable. The inequitable distribution of the benefits and costs of technology have become highly visible in the form of dot.com millionaires and corporate downsizing. Resurgence of environmentalism today may lead to new demands for better anticipation and management of technology. The TF toolkit is expanding—old tools retain value but are being supplemented by powerful new tools that exploit electronic information resources and deal with complex systems and apparently chaotic behavior. Platforms for TF are changing and becoming much more integrated with company functions and policy setting. There is growing recognition that the organizational processes of deriving and implementing technology roadmaps, competitive technological intelligence, and national foresight should be valued more than the accuracy of the forecasts.

B. DEVELOPMENT OF TF

Perhaps the first official account of a systematic outlook on the future of science and technology occurred in 1935 through the New Deal’s National Resource Commission, which tasked a committee to look into the future of 13 major inventions. The resulting report sought to predict the economic and social impact of these emerging technologies [1]. The report was widely publicized in the business press and one can infer that the concern at that time was primarily about the effects of technological change [2]. After World War II Vannevar Bush presented the U.S. scientific enterprise with a blueprint for post-war science policy by depicting a model of innovation in which technology flows from basic science to product development and commercialization [3]. The depiction of a linear and causal relationship between investments in basic science and technological innovation held in abeyance concern over the direction of technological change, while concentrating mostly on the rate of technological change, particularly following the Sputnik shock. This emphasis also catered to the needs of the U.S. defense establishment, where directional uncertainties were minimized given the Cold War focus on successive generations of weapons systems. As a consequence, first generation R&D management strategy in both industry and government had strong input; its emphasis was on funding research, setting up labs, and establishing research teams [4].

Cold War competition brought forth the need to cope with dramatic developments in technology such as guided missiles, nuclear weapons, and computing. Systems analysis became an important tool in designing such complex systems. The military–industrial complex needed ways of anticipating levels of performance in weapons and components, and ways to set feasible performance goals.



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol.2, Special Issue 5, October 2014

Sl.no:	Families	Methods
1	Expert Opinion	Delphi (iterative survey), Focus Groups [panels, workshops], Interviews, Participatory Techniques
2	Trend Analysis	Trend Extrapolation [Growth Curve Fitting], Trend Impact Analysis, Precursor Analysis, Long Wave Analysis
3	Monitoring & Intelligence	Monitoring [environmental scanning, technology watch]
4	Statistical	Correlation Analysis, Demographics, Cross Impact Analysis, Risk Analysis, Bibliometrics [research profiling; patent analysis, text mining]
5	Modeling & Simulation	Agent Modeling, Cross Impact Analysis, Sustainability Analysis [life cycle analysis], Causal Models, Diffusion Modeling, Complex Adaptive System Modeling (CAS) [Chaos]
6	Scenarios	Scenarios [scenarios with consistency checks; scenario management] Scenario-simulation [gaming; interactive scenarios], Field Anomaly Relaxation Method [FAR]
7	Valuing/Decision/Economics	Relevance Trees [futures wheel], Action [options] Analysis, Cost-benefit analysis, Decision analysis [utility analyses], Economic base modeling [input-output analysis]
8	Descriptive and Matrices	Analogies, Backcasting, Checklist for Impact Identification, Innovation System Modeling, Institutional Analysis, Mitigation Analysis, Morphological Analysis, Roadmapping [product-technology roadmapping],
9	Creativity	Brainstorming [brainwriting; nominal group process (NGP)], Creativity Workshops [future workshops], TRIZ, Vision Generation

By 1949, largely under the aegis of the U.S. government, the development of TF as a systematic means of exploring the future of technology was under way. Grounded in systems analysis, TF helped military strategists deal with the complexity and long lead times necessary to develop modern armaments and anticipate probable countermeasures. During the next decade, the focus was on forecasting the rate of technological change. Quantitative exploratory methods, working from the past to the future, included trend extrapolation, leading indicators, and growth models. But normative forecasting, starting with perceived future needs, played a role as well. The mix also fostered more qualitative approaches such as relevance trees [5], mission flow analysis, scenario writing, and Delphi [6]. First textbooks on TF described not only these tools but placed them into the planning and decision making context as well [7, 8].

V. METHODS OF TECHNOLOGY FORECASTING

There are hundreds of TF Methods, which can be fit into 9 families [2]: Expert Opinion, Trend Analysis, Monitoring & Intelligence, Modeling & Simulation, Scenarios, Statistical, Descriptive, Creativity, and Valuing/Decision/Economics Methods. [5] lists methods in each family as:

We will now briefly review some of the most popular traditional methods include environmental scanning, models, scenarios, Delphi, extrapolation, probabilistic forecasts, technology measurement etc. Recent advances in TF will be discussed in the next section.

DELPHI

Delphi remains a popular technique for preparing forecasts. One of the most significant applications of Delphi within the past decade has been the preparation of massive national forecasts in Korea, Japan, Germany and India [9, 10]. One significant methodological advance in use of Delphi was developed by Dransfeld et al. [11]. They used Bayesian weighting to combine responses to a Delphi questionnaire. They weighted the responses of the panel members on four different factors: experience in the industry, position in the company, position of the company in the industry, and self-rating on each question. For different questions, the ratings of the company in the industry would



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol.2, Special Issue 5, October 2014

vary and self-ratings might vary. For each factor, the panel members were rated in one of five categories, designated A through E, in decreasing level of expertise.

EXTRAPOLATION

Forecasting by extrapolation means that the forecaster assumes that the past of a time series contains all the information needed to forecast the future of that time series. An appropriate model is fitted to the historical data and the projection of that model becomes the forecast. Selecting the appropriate model for extrapolation is critical to forecasting success. If the wrong model is chosen, no amount of data accuracy or sophisticated fitting methods can save the forecast. The two growth curves most commonly used by technological forecasters are the logistic or Pearl and the Gompertz.

ENVIRONMENTAL SCANNING

Forecasting by environmental scanning takes advantage of the fact that technological change often follows a standard sequence of steps. A typical sequence might be: Theoretical proposal, Scientific findings, laboratory feasibility, Operating prototype and Commercial introduction. By observing a technological innovation at an early stage in this sequence, it may be possible to anticipate when it will reach later stages in the sequence, or at least provide warning that further developments may follow. A major advance of the past few years has been using a computer for the "grunt work." Searching the literature can now be automated. Data mining (DM) and database tomography (DT) have become practical techniques for assisting the forecaster to identify early signs of technological change.

VI. RECENT ADVANCES IN TF

A KEYWORD - BASED MORPHOLOGICAL ANALYSIS

Conventional TF techniques utilized for seeking new technology opportunities are generally characterized by nonquantified feature, they must be further coupled with quantitative methods or supported by concrete data. To this end, patent analysis is actively employed in excavating promising technology, but this method is subject to limitations because bibliometric analysis focuses on conducting analysis at a macrolevel and in a statistical manner and thereby poses problems when entering into a more microlevel analysis, such as for new technology development. As a remedy, a keyword-based MA, which improves the original MA by adopting text mining to patent documents and by considering the information of related technologies and companies was proposed. [5]

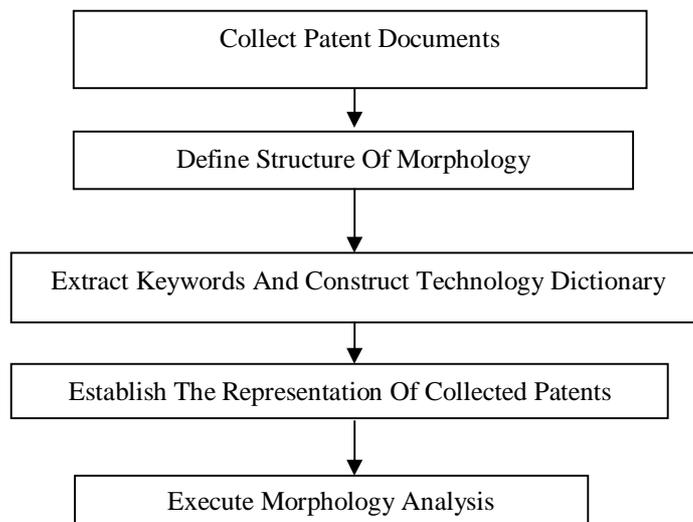


Fig.1. Framework for keyword-based MA



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol.2, Special Issue 5, October 2014

B PATENT DOCUMENTS USING LINK STRUCTURE

Studying link structure of the World Wide Web (WWW) is an area which has attracted a lot of interest in recent times. Several papers have been published on structural analysis of hyperlinked environments such as the WWW. The WWW can be modeled as a graph and valuable information can be derived by analyzing links between the web-pages primarily for the purpose of building better search engines. Many novel methods have been presented to discover communities from the WWW and discover authoritative web-pages. Citation analysis is a branch of information science on which plenty of research has been done. Citation analysis pertains to analysis of articles and research paper citations in a scholarly field and deriving useful information from it. It has primarily been used as a useful tool to quantify and judge the impact of a paper or a journal. The work presented in this paper lies at the intersection of the two fields: structural analysis of WWW and citation analysis. In this paper, we present a method for classifying documents (such as articles and patents containing references) to a class or topic based on their link structure, references and citations. The method consists of analyzing the link structure of a corpus to first identify authoritative papers and assigning a class label to them. The class labels are assigned manually by a domain expert by going through the respective documents. The next step consists of identifying related papers to the authoritative papers using citation analysis. The authoritative papers, their class labels and their related papers constitute a model. Papers for which class label needs to be determined are classified based on the created model.

The proposed algorithm for predicting or assigning class label to an unseen document is a two phase process. Phase I consists of building a model using a corpus (training data), which is a collection of academic publications or patents which have references. Model building is a multi-step process that makes use of techniques such as PageRank algorithm for determining authoritative pages, using co-citation analysis and bibliographic coupling for finding papers in the training data that are similar to the authoritative papers. The trained model is then used to predict community memberships for new documents in the second phase (called as scoring).

C PATENT DOCUMENTS USING MATRIX MAP AND PATENT CLUSTERING

Most TF models are based on qualitative and subjective methods such as Delphi. That is, there are few objective models. The authors use patent documents as objective data to develop a model for vacant TF. The paper attempts to objectively forecast the vacant technology areas in a given technology field. This paper proposes a quantitative and objective TF model that employs patent documents as objective data and a matrix map and KM-SVC as quantitative methods. To verify the performance of the matrix map and KM-SVC, the authors conduct an experiment using patent documents related to MOT (the given technology field in this paper). The results suggest that the proposed forecasting model can be applied to diverse technology fields, including R&D management, technology marketing, and intellectual property management.

The methodology involves four steps. First, we use text-mining techniques to preprocess MOT patent documents. Second, by using the technology classification results for MOT, we develop a matrix map for forecasting the vacant technology areas in MOT. Third, we cluster NOT patent documents by using KM-SVC and define the detailed technology areas in each cluster by using the top five keywords. Fourth, to determine the vacant technology areas in MOT, we combine the results from the second and third steps. We select the vacant technology areas from vacant or relatively small areas indicated by the matrix map and KM-SVC results. Although we focus on MOT as the given technology field for vacant TF, the results can be applied to any technology field.

D PATENT ANALYSIS USING BAYESIAN NETWORK (BN) MODELS

The BN is a graphical model to find novel associations between variables [13, 14]. This is based on statistical probability distributions. Using the joint distribution of entire attributes given by Bayes' formula, we construct a BN model. In our research, we use the International Patent Classification (IPC) codes of patent documents for the variables of the BN model. The IPC code is a hierarchical structure of technology in patent documents [15]. We compute the joint probability distribution of IPC codes to get the relationships between them. The BN results for IPC codes give the technological associations between them, and we can use these results for technology management.



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol.2, Special Issue 5, October 2014

To verify the performance of our method, we performed a case study using the patent documents applied for by the BMW company. We constructed the BN model to explain the technological relationships that exist in the patent data of BMW. The company could potentially use this technological information for technology management such as R&D planning and new product development.

VII. CHOOSING A FORECASTING METHOD

A large number of methods have evolved for TF, but the quality of forecasts greatly depends on proper selection and application of appropriate methods. The application demands that the technique used need to be time-, space- and technology-specific. Yet, there is little research done on matching the TF methods techniques to a particular technology. One such study comes from, Levary and Han [6], who have considered three basic factors, namely the extent of data availability, the degree of data validity and degree of similarity between proposed technology and existing technologies. Each factor has been categorized into cases as small/low, medium/moderate, large/high and their combinations. According to [6], given a small amount of low or medium validity data, and no similarity between proposed technology and existing technologies, a reasonable choice is a method based on information obtained from a panel of experts.

A more recent study [16] provides a comprehensive procedure to pick the right TF method: First they identify the characteristics of a technology that need to be considered (rate of change, ease of diffusion, number of alternatives available, etc). Next, using a 10-point scale, experts of the selected technology rate each of the characteristics for the selected technology. Then, using the same characteristics, experts of TF methods rate every method in the same manner. Finally, the profiles for the TF methods and technology profiles are superimposed to ascertain the "best fit," i.e., the technique profile that closely matches the technology profile.

As we defined earlier, bibliometrics is the statistical analysis of text documents, typically publications and patents. Since publications in this case refers mainly to academic publications and patents, science and technology intensive industries would logically be a better fit for this type of analysis. As patents and publications often deal with ideas and techniques in the relatively early stages of development, this is the stage at which bibliometric methods are most useful. Also, in the early stages of development, technical merit is probably the key determinant of success. Later on many other factors would influence the success of a technology or product, so there is a lot more complexity and noise. In such situations, "higher-level" features and pattern recognition techniques become more appropriate.

VIII. SUMMARY

There has been significant progress in technological forecasting methodology using patent analysis over the last decade. Some of this progress represents improvements in existing techniques, such as morphology analysis, text mining, extrapolation and environmental scanning.

REFERENCES

1. Becker, P.R. (2009), "Technology management degree programs: meeting the needs of employers", *Proceedings of PICMET 2009*, pp. 2171-83.
2. Bengisu, Z. and Nekhili, R. (2006), "Forecasting emerging technologies with the aid of science and technology databases", *Technological Forecasting and Social Change*, Vol. 73 No. 7, pp. 835-44.
3. Ben-Hur, A., Horn, D., Siegelmann, H.T. and Vapnik, V. (2001), "Support vector clustering", *Journal of Machine Learning Research*, Vol. 2, pp. 125-37.
4. Camus, C. and Brancalion, R. (2003), "Intellectual assets management: from patents to knowledge", *World Patent Information*, Vol. 25 No. 2, pp. 155-9.
5. Chatratana, S. (2009), "Keynote: management of technology", *Proceedings of ECTI-CON 6th International Conference on Electrical Engineering, Electronics, Computer, Telecommunications and Information Technology*, Vol. 2, pp. xxxv-xxxvi.
6. Cherkassky, V. and Mulier, F. (1998), *Learning from Data Concepts, Theory, and Methods*, Wiley, New York, NY.
7. Coates, V., Farooque, M., Klavans, R., Lapid, K., Linstone, H.A., Pistorius, C. and Porter, A.L. (2001), "On the future of technological forecasting", *Technological Forecasting and Social Change*, Vol. 67, pp. 1-17.
8. Cyert, R.M. and Kumar, P. (1994), "Technology management and the future", *IEEE Transactions on Engineering Management*, Vol. 41 No. 4, pp. 333-4.



ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol.2, Special Issue 5, October 2014

9. Ernst, H. (2001), "Patent applications and subsequent changes of performance: evidence from time-series cross-section analyses on the firm level", *Research Policy*, Vol. 30, pp. 143-57.
10. Fattori, M., Pedrazzi, G. and Turra, R. (2003), "Text mining applied to patent mapping: a practical business case", *World Patent Information*, Vol. 25, pp. 335-42.
11. Glenn, J.C. and Gordon, T.J. (2003), *Futures Research Methodology*, American Council for UNU, Washington, DC.
12. Han, J. and Kamber, M. (2005), *Data Mining: Concepts and Techniques*, Morgan Kaufmann, San Francisco, CA.
13. Hastie, T., Tibshirani, R. and Friedman, J. (2001), *The Elements of Statistical Learning, Data Mining, Inference, and Prediction*, Springer, New York, NY.
14. Hua, Z., Yang, J., Coulibaly, S. and Zhang, B. (2006), "Integration TRIZ with problem-solving tools: a literature review from 1995 to 2006", *International Journal of Business Innovation and Research*, Vol. 1 Nos 1/2, pp. 111-28.
15. Indukuri, K.V., Mirajkar, P. and Sureka, A. (2008), "An algorithm for classifying articles and patent documents using link structure", *Proceedings of International Conference on Web-Age Information Management*, pp. 203-10.
16. McDermott, C.M., Kang, H. and Walsh, S. (2001), "A framework for technology management in services", *IEEE Transactions on Engineering Management*, Vol. 48 No. 3, pp. 333-41.