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Comparison of Different Performance Measures of Complex Product Systems in Technology Forecasting

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Abstract

Technology forecasting estimates the future value of characteristics and performance of a technology. Since technologies are embedded in products, different measures of these products can be used in technology forecasting. Two classes of data play a central role in technology forecasting studies. In the first class, publications and patents are commonly excepted measures as indicators of scientific and technological performance. The second class is the performance data of the “technology in use”. In this second type of data, performance is usually characterized by multiple parameters in a complex product system since these product systems are the aggregates of subsystems. Technological progress obtained by these two types of datasets may show different patterns. Also each parameter of the overall system may show different pattern either. Authors claim that, in order to improve the quality of technology forecasts, both datasets should be studied. A multidimensional technology life cycle should be considered before taking managerial decisions. In this study an application of a refrigerator system has been performed to investigate the authors’ claim. Three types of datasets, patents from first type of dataset; coefficient of performance (COP) and electric efficiency index (EEI) from second type of dataset are used. Different life cycles and different scenarios of the same system are obtained using growth curves as a technology forecasting tool. Findings are discussed and the proposed model of using measures in technology forecasting is explained in detail.

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Keywords: Technology Forecasting, S-Curves, Measurement, Complex Product System

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1. Introduction

Forecasting a technology means estimating the future value of some parameters which characterizes the performance of that technology and provides a timely insight of technology change (J. P. Martino, 1993; Watts & Porter, 1997). Indicators can measure these technological changes for technology forecasting studies. While the dominant approach is using patent applications over time as an indicator, some researchers use different performance criteria to understand technological progress.

A technology executes its base principle to fulfil a human purpose (Arthur, 2007). Since technologies are embodied in products, to execute this base principle, technology performance indicators of these products can be used as a measure of technological progress. Depending on the complexity of the technology, sometimes a single parameter is insufficient to measure whole technological progress. Complex product systems have more than one system level performance parameters related to technology. In this paper, authors demonstrate the need of different measures to improve the quality of technology forecasts through a case study on refrigeration technologies. A complex product system is modelled by using different datasets. Paper focuses on using multiple indicators to have a better insight for future progress. The plan of this study is as follows. Seminal works on technology forecasting and existing approaches on measurements are reviewed in the second section, research model is explained in the third section, an application of the proposed methodology and its results are discussed in the fourth section and finally section five presents conclusions and future works.

2. Literature Review

As can be seen in Fig.1 technology cycle begins with a technological discontinuity. In the introduction stage, the progress of technology is often slow and it is characterized by low performance. This growth stage takes place after the technology has proven its utility and the pace of improvement quickens during this stage. In this period of ferment during which rivalry and competition among variations of the original breakthrough eventually lead to the selection of a single dominant configuration (Abernathy & Utterback, 1978). The technology is widely adopted leading the change in the nature of competition. Following this period, incremental evolution takes place of the fast progress of technology. And the cycle of variation, selection and retention begins again with a further technological discontinuity (Murmann & Frenken, 2006). In this last period, the technology asymptotically approaches a natural performance limit and progress stops. The stage where the existing technology reaches its full potential defines the end of technology life.

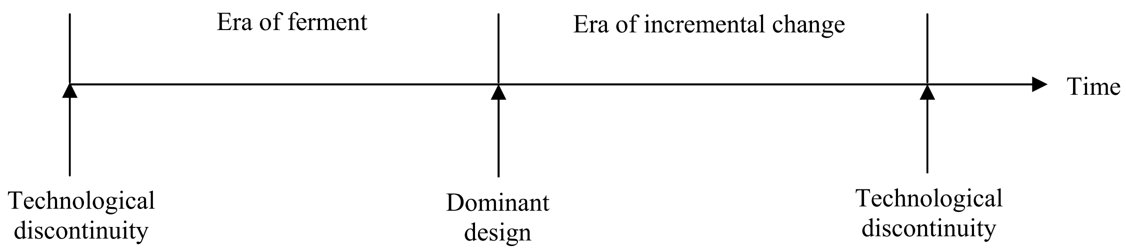

Fig. 1. The technology cycle (P. Anderson & Tushman, 1990)

Within technology cycle, technology forecasting deals with the timeline of the prospects of the technology. Martino (1993) defined four elements of a technology forecast; the technology being forecasted, the time of the forecast, a statement of the characteristics and a statement of the probability associated with the forecast. Since then, a variety of quantitative and qualitative techniques have been developed. Environmental scanning, casual models, scenarios, delphi, extrapolation, analogy and probabilistic models are widely used in literature (Martino, 2003). In quantitative techniques, indicators of technological performance is used to model the current state of technology and used to forecast future performance. One of the most challenging parts of technology forecasting is obtaining data, since publicly available historical data is scarce. Therefore patents and publications are useful sources in providing significant data for emerging technologies (Tugrul U. Daim, Rueda, Martin, & Gerdsri, 2006). Many researchers use bibliometric data for analysing technological pattern in their studies (Chen, Chen, & Lee, 2011; Tugrul U Daim, Ploykitikoon, Kennedy, & Choothian, 2008; Dubarić, Giannoccaro, Bengtsson, & Ackermann, 2011; Gao et al., 2013; Kucharavy & De Guio, 2011; Trappey, Wu, Taghaboni-Dutta, & Trappey, 2011).

Substantial work on technological progress has been done by performance data of the "technology in use". For example, seat-miles-per-year capacity for aircrafts, CPU cycle times for minicomputers and barrels per day for cement kilns are used as performance criteria by Tushman and Anderson (1986). But in literature it can be seen that complex product systems are characterized by multiple parameters. Researchers, who are able to access different performance parameters for complex product systems, use multiple indicators of technological characteristics. Sahal (1981) analysed performance improvements for tractors, using average fuel consumption efficiency, average fuel mechanical efficiency and per gallon of fuel used, ratio of drawbar horsepower to belt horsepower, or horsepower to weight ratio. T. R. Anderson, Daim, and Kim (2008) utilized channel bandwidth, number of channels, channel bit rate, transmission power, number of speech channels and data capacity as technical performance parameters for forecasting wireless technologies. Yoon et al. (2013) forecasted single-lens reflex camera technology using data envelopment analysis by employing resolution, max FPS, focus point, weight and MSRP data. Similarly, Hsu and Chang (2014) examine environmental, technological, economical and societal characteristics of hydrogen storage technologies and obtain data by fuzzy Delphi method.

Some researchers stated different measures of technologies. Sahal (1977a) expressed multidimensional performance characteristics of technologies and Martino (1993) tried to obtain a single composite measure from these different performance measurements of aircraft technology. Lately Suominen and Seppänen (2014) discussed the accuracy of bibliometric data versus actual development. In summary, there exist many measurements to follow technological progress and each of them provides significant information for technology forecasting in order to increase the accuracy. This perspective encourages researches to use multiple indicators to have a better insight for future progress.

3. Research Model

As can be seen in literature section, the life of a main system is usually forecasted through the trend of a single parameter. However in a complex product system, it is impossible to represent all technology progress with one single technology life cycle (Taylor & Taylor, 2012). This paper shows different life cycles of each performance parameters of the main system and authors suggest that a multidimensional analysis should be applied in order to decrease the uncertainty of the technology forecast. In this research, refrigeration technology will be used to investigate the use of multi-indicators for technology performance in forecasting. The model proposed examines the technology progress regarding different performance measures of the same system and compares the life cycles obtained by each dataset. As a first step of the study, dataset is obtained from refrigerator patent analysis.

Technological change is regarded as a change in functional performance characteristics of overall system, and functional specifications must show the overall system performance rather than a sum of material and physical component performance (Sahal, 1977b). Since a complex product system has many functions, performance characteristics should be multidimensional. As a second step of the study, overall performance characteristics will be identified.

After obtaining all performance data from both datasets, a technology forecasting method will be applied to predict the future behavior of technological progress. S curve model fits into this purpose and is used to model derived data.

S curve is a useful tool which symbolize technology's life depending on the law of natural growth by using simple logistic equations (Kucharavy & De Guio, 2011). In the early stages of technology, performance is slow, when the technology is better understood, the rate of improvement increases and finally technology approaches its limits (Christensen, 1992; Sahal, 1981).

4. An Application on Domestic Refrigerator Technologies

As a complex product system, domestic refrigerator is studied and refrigeration technology is examined at this paper. A domestic refrigerator executes its base principle to fulfil refrigeration process. Basic principle of refrigeration system is based on the second law of thermodynamics. A standard domestic refrigerator has a vapour compression refrigeration system as illustrated in Fig. 2. In a vapour compression cycle, a circulating refrigerant enters a compressor as low-pressure vapour and after compression, it exits the compressor as high pressure superheated vapour (Gomathi, Parameshwari, & Anandh, 2013). The superheated vapour flows through the condenser, where it condenses from vapour form to liquid form, giving off heat in the process (Yeh, 2014). High-pressured refrigerant leaves the condenser at slightly above room temperature and enters expansion valve where its pressure decreases. Then refrigerant goes to the evaporator, which absorbs heat into the system, which causes the refrigerant to vaporize. When refrigerant is boiled at a lower temperature than that of the substance to be cooled, it absorbs heat from the substance (Whitman, Johnson, & Tomczyk, 2005). The vaporized refrigerant goes back to the compressor to restart the cycle (Yeh, 2014). This refrigeration process helps to identify performance parameters of the domestic refrigerator.

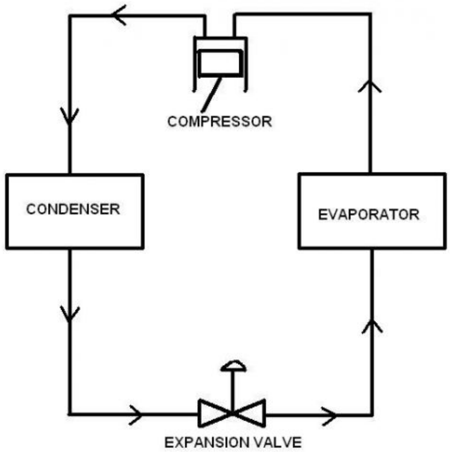

Fig. 2. Vapor compression refrigeration system

First, patent analysis is used in order to obtain first type of dataset. International patent applications are found in PatentScope database of World Intellection Property Organization (WIPO) ("Search International and National Patent Collections," 2014) and count data is utilized.

Second type performance parameters are determined by interviewing with experts working at Research and Development department of a refrigerator manufacturer. Coefficient of performance (COP) and Electric Efficiency Index (EEI) are chosen as overall performance criteria.

- *Coefficient of Performance*: The energy efficiency of a refrigeration process indicated by its coefficient of performance (COP). It is the ratio of the heat rejected by the condenser to the electricity consumption of the compressor (Westra, 1993). Simply it's found as how much heat we can take away from the colder heat reservoir divided by how much energy must be wasted as the work. The greater this number, the higher the efficiency. The limit of COP is set by thermodynamic principles is determined as 2.9 in the conditions of this study.

$$COP = \frac{Q_c}{W} \tag{1}$$

where Q_c stands for exchanged heat by condenser and W is work input to compressor.

- *Energy Efficiency Index*: Comparing energy consumption data of products is quite complex, and need to be standardized for an accurate comparison. Energy efficiency index takes into account primarily energy consumption, the volume and the lowest temperature of different compartments. This makes all refrigerators comparable. For domestic refrigerators the energy efficiency index (EEI) is set at 102 for the average model on the market in year 1992 (Bertoldi & Atanasiu, 2007). After obtaining COP and EEI data for domestic refrigerator per year, growth curve model has been applied. Only for patent data, limit is determined from historical data. Then data are normalized and limits are set as 1. Then S-curves are derived for each dataset.

4.1. Results

S-curve equations obtained from historical data of each dataset are shown in Table 1 below.

Table 1. Logistic equations of s-curves

Dataset	S-curve Equation
Patent data	$1/(1+e^{-46,49t-2018})$
COP data	$1/(1+e^{-75,76t-2000})$
EEI Data	$1/(1+e\text{-}^{40,06t-2004})$

The graphs belong to these s-curves of technology life cycles can be seen in Fig. 3. Green curve belongs to EEI, blue curve is for COP and black curve is obtained by patent data.

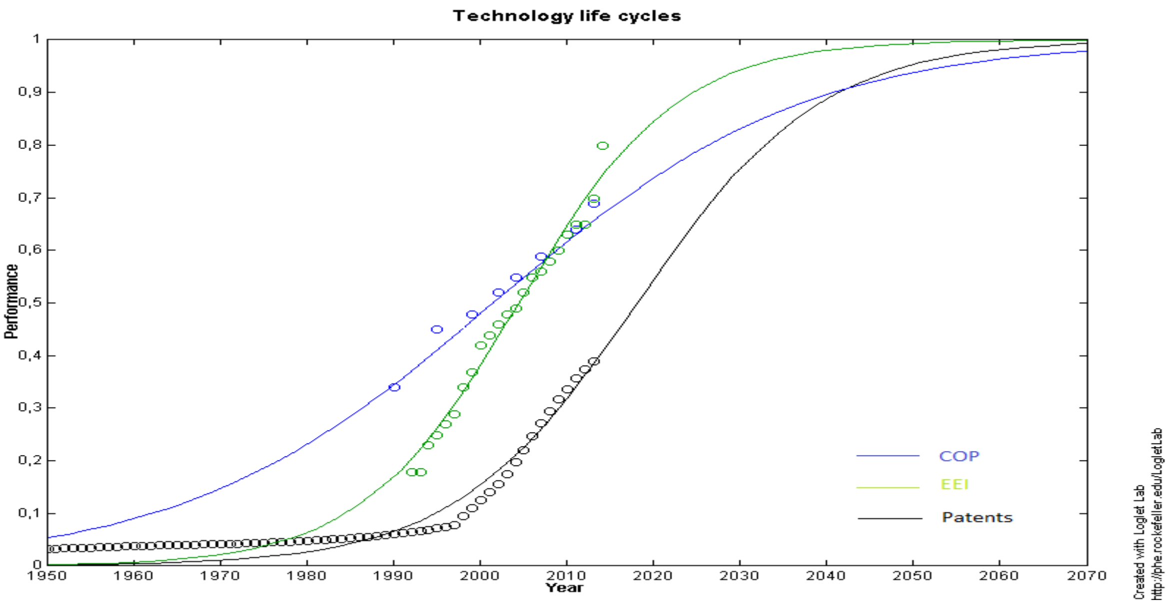

Fig. 3. Technology s –curves of refrigeration technologies

S-curve indicates that, the fastest growth in technology occurs in midpoint, and after that growth rate begins to slow down and eventually saturates. As it can be seen from Fig. 3, midpoint is found as 2000 from COP data, 2004 from EEI data and 2018 from patent data, which imply different scenarios. Similarly refrigeration technology approaches its limits about 2060, 2040 and 2055 respectively found by EEI, COP and patent data. This result shows that, forecasts may change by the kind of data used, and especially in long-term forecasts there exists bigger differences.

5. Conclusion and Future Research

The purpose of this paper is to demonstrate the challenges of using different datasets in technology forecasting. Authors obtained different technology life cycles of same technology, which are inconsistent with each other. Particularly, in long-term forecasts, incompatible results could affect managerial decisions negatively. In order to decrease the uncertainty and to acquire better forecasts, authors suggest studying all performance criteria together to derive a multidimensional technology forecast. In this manner a forecaster can have more scenarios, which helps managers to get ready to all possible situations for their company. Further research should focus on, how to combine all datasets to determine the most possible scenario, and also obtaining probabilities of each state of progress. In addition, different technology forecasting techniques can be experienced to investigate the authors' claim.

References

Abernathy, W. J., & Utterback, J. M. (1978). Patterns of industrial innovation. *Journal Title: Technology review. Ariel, 64*, 254.228.

Anderson, P., & Tushman, M. L. (1990). Technological discontinuities and dominant designs: A cyclical model of technological change. *Administrative science quarterly*, 604-633.

Anderson, T. R., Daim, T. U., & Kim, J. (2008). Technology forecasting for wireless communication. *Technovation, 28*(9), 602-614.

Arthur, W. B. (2007). The structure of invention. *Research policy, 36*(2), 274-287. doi: 10.1016/j.respol.2006.11.005

Bertoldi, P., & Atanasiu, B. (2007). Electricity consumption and efficiency trends in the enlarged European Union. *IES–JRC. European Union*.

Chen, Y.-H., Chen, C.-Y., & Lee, S.-C. (2011). Technology forecasting and patent strategy of hydrogen energy and fuel cell technologies. *International Journal of Hydrogen Energy, 36*(12), 6957-6969. doi: 10.1016/j.ijhydene.2011.03.063

Christensen, C. M. (1992). Exploring the Limits of the Technology S-Curve. Part I: Component Technologies. *Production and Operations Management, 1*(4), 334-357.

Daim, T. U., Ploykitikoon, P., Kennedy, E., & Choothian, W. (2008). Forecasting the future of data storage: case of hard disk drive and flash memory. *foresight, 10*(5), 34-49.

Daim, T. U., Rueda, G., Martin, H., & Gerdsri, P. (2006). Forecasting emerging technologies: Use of bibliometrics and patent analysis. *Technological Forecasting & Social Change, 73*(8), 981-1012. doi: 10.1016/j.techfore.2006.04.004

Dubarić, E., Giannoccaro, D., Bengtsson, R., & Ackermann, T. (2011). Patent data as indicators of wind power technology development. *World Patent Information, 33*(2), 144-149. doi: 10.1016/j.wpi.2010.12.005

Gao, L. D., Porter, A. L., Wang, J., Fang, S., Zhang, X., Ma, T. T., . . . Huang, L. (2013). Technology life cycle analysis method based on patent documents. *Technological forecasting & social change, 80*(3), 398-407. doi: 10.1016/j.techfore.2012.10.003

Gomathi, D., Parameshwari, P., & Anandh, A. V. (2013). A Novel Refrigerator System for Busy People. *International Journal of Emerging Technology and Advanced Engineering, 3*(1).

Hsu, C.-W., & Chang, P.-L. (2014). *An evaluation model of hydrogen storage technology by a fuzzy Delphi method.* Paper presented at the Management of Engineering & Technology (PICMET), 2014 Portland International Conference on.

Kucharavy, D., & De Guio, R. (2011). Application of S-shaped curves. *Procedia Engineering, 9*, 559-572.

Martino, J., P. (1993). *Technological Forecasting for Decision Making* (3rd ed.): Mcgraw-Hill, Inc.

Martino, J. P. (1993). A comparison of two composite measures of technology. *Technological Forecasting and Social Change, 44*(2), 147-159.

Martino, J. P. (2003). A review of selected recent advances in technological forecasting. *Technological Forecasting and Social Change, 70*(8), 719-733.

Murmann, J. P., & Frenken, K. (2006). Toward a systematic framework for research on dominant designs, technological innovations, and industrial change. *Research policy, 35*(7), 925-952.

Sahal, D. (1977a). The multidimensional diffusion of technology. *Technological Forecasting and Social Change, 10*(3), 277-298.

Sahal, D. (1977b). A theory of measurement of technological change. *International Journal of Systems Science, 8*(6), 671-682.

Sahal, D. (1981). *Patterns of technological innovation*. Reading, Mass: Addison-Wesley Pub. Co., Advanced Book Program/World Science Division.

Search International and National Patent Collections. (2014). Retrieved 12.12.2014, from World Intellectual Property Organization http://patentscope.wipo.int/search/en/search.jsf

Suominen, A., & Seppänen, M. (2014). Bibliometric data and actual development in technology life cycles: flaws in assumptions. *foresight, 16*(1), 37-53.

Taylor, M., & Taylor, A. (2012). The technology life cycle: Conceptualization and managerial implications. *International Journal of Production Economics*.

Trappey, C. V., Wu, H.-Y., Taghaboni-Dutta, F., & Trappey, A. J. C. (2011). Using patent data for technology forecasting: China RFID patent analysis. *Advanced Engineering Informatics, 25*(1), 53-64. doi: 10.1016/j.aei.2010.05.007

Tushman, M. L., & Anderson, P. (1986). Technological discontinuities and organizational environments. *Administrative science quarterly*, 439-465.

Watts, R. J., & Porter, A. L. (1997). Innovation forecasting. *Technological Forecasting & Social Change, 56*(1), 25-47. doi: 10.1016/S0040-1625(97)00050-4

Westra, D. G. (1993). COP improvement of refrigerator/freezers, air-conditioners, and heat pumps using nonazeotropic refrigerant mixtures.

Whitman, W. C., Johnson, W. M., & Tomczyk, J. A. (2005). *Refrigeration & air conditioning technology*: Cengage Learning.

Yeh, R. (2014). Compression Refrigeration System. Retrieved 08 January, 2015, from http://web.mit.edu/2.972/www/reports/compression_refrigeration_system/compression_refrigeration_system.html

Yoon, B. S., Charoensupyan, A., Hu, N., Koosawangsri, R., Abdulai, M., & Wang, X. (2013). *Technology forecasting of digital single-lens reflex camera market: The impact of segmentation in TFDEA.* Paper presented at the Technology Management in the IT-Driven Services (PICMET), 2013 Proceedings of PICMET'13:.