Technological Forecasting – A Review

Ayse Kaya Firat
Wei Lee Woon
Stuart Madnick

Working Paper CISL# 2008-15

September 2008

Composite Information Systems Laboratory (CISL)
Sloan School of Management, Room E53-320
Massachusetts Institute of Technology
Cambridge, MA 02142

TECHNOLOGICAL FORECASTING – A REVIEW

Ayse Kaya Firat, Stuart Madnick, Wei Lee Woon
September 2008

ABSTRACT

This report aims to summarize the field of technological forecasting (TF), its techniques and applications by considering the following questions:

- What are the purposes of TF?
- Which techniques are used for TF?
- What are the strengths and weaknesses of these techniques / how do we evaluate their quality?
- Do we need different TF techniques for different purposes/technologies?

We also present a brief analysis of how TF is used in practice. We analyze how corporate decisions, such as investing millions of dollars to a new technology like solar energy, are being made and we explore if funding allocation decisions are based on "objective, repeatable, and quantifiable" decision parameters. Throughout the analysis, we compare the bibliometric and semantic-enabled approach of the MIT/MIST Collaborative research project "Technological Forecasting using Data Mining and Semantics" (TFDMS) with the existing studies / practices of TF and where TFDMS fits in and how it will contribute to the general TF field.

1. INTRODUCTION

TF, in general, applies to all purposeful and systematic attempts to anticipate and understand the potential direction, rate, characteristics, and effects of technological change, especially invention, innovation, adoption, and use. One possible analogy for TF is weather forecasting: Though imperfect, TF enables better plans and decisions. A good forecast can help maximize gain and minimize loss from future conditions. Additionally, TF is no more avoidable than is weather forecasting. All people implicitly forecast the weather by their choice of whether to wear a raincoat, carry an umbrella, and so on. Any individual, organization, or nation that can be affected by technological change inevitably engages in forecasting technology with every decision that allocates resources to particular purposes.

Formation of research strategies can greatly benefit from TF studies that identify technologies with the greatest potential. To facilitate the formation of such strategies, MIT and MIST started a collaborative research project called "Technological Forecasting using Data Mining and Semantics" (TFDMS) [1]. The study focuses on novel methods for automatically mining science and technology information sources with the aim of extracting patterns and trends. The goals include (but are not limited to) generating growth forecasts for technologies of interest, intuitive representations of interrelationships between technology areas, identification of influential researchers or research groups and the discovery of underlying factors, which may affect or stimulate technological growth. The aim is to develop a suite of techniques, which will significantly extend and improve existing methods for performing so-called "tech-mining".

This report aims to summarize the vast field of TF, its purposes, evolution, techniques and applications. We start with a brief explanation of the purposes of TF, and continue with its evolution and popular methods, applications and end up with where / how MIT/MIST project fits in and contributes to the general TF field.

1.1. THE NEED FOR AND THE DIVERSE PURPOSES OF TF

Analyses of emerging technologies and their implications inform critical choices ranging from the multinational level (e.g., the European Union) to the individual organization (e.g., a company). For example, large companies need TF, in its various guises, to:

- Prioritize R&D,
- Plan new product development,
- Make strategic decisions on technology licensing, joint ventures, and so forth.

Small companies also depend on technological innovation for their existence. In these companies, TF methods are used to forecast adoption or diffusion of innovations, where parameters such as rate of imitation by other adopters or rate of response to advertising can be measured. TF studies in companies are often called Competitive Technological Intelligence (CTI or TI).

In addition to the effort by businesses to map out commercially viable roadmaps for technological development, the TF field includes more social and diffuse measurements as well. For example, governments use national foresight studies to assess the course and impact of technological change for the purposes of effecting public policy. This includes what is known as technology assessment (TA) or social impact analysis, which examines the likely long-term effects of technological development as its impact spreads throughout society.

Furthermore, some academic futures studies aim general consciousness raising whereas governments seek to use Tech Foresight as a tool to improve networks and build consensus in the science and technology (S&T) communities or in national, regional, or sectoral innovation systems. Tech Foresight studies are also used as an awareness-raising tool, alerting industrialists to opportunities emerging in S&T or alerting researchers to the social or commercial significance and potential of their work [2].

1.2. FUTURE ORIENTED TECHNOLOGY ANALYSIS (FTA)

There are many overlapping forms of forecasting technology developments and their impacts, including technology intelligence, forecasting, roadmapping, assessment, and foresight. There has been little systematic attention to the conceptual development of the field as a whole. Since 2003, the Technology Futures Analysis Methods Working Group[1] (TFAMWG) has sought to lay a framework from which to advance the processes and the methods used in technology futures analysis (TFA). They define these overlapping forms as [3]:

- Technology monitoring, technology watch, technology alerts (gathering and interpreting information)
- Technical intelligence and competitive intelligence (converting that information into usable intelligence)
- Technology forecasting (anticipating the direction and pace of changes)
- Technology roadmapping (relating anticipated advances in technologies and products to generate plans)

[1] Alan L. Porter (U.S.), W. Bradford Ashton (U.S.), Guenter Clar (EC & Germany), Joseph F. Coates (U.S.), Kerstin Cuhls (Germany), Scott W. Cunningham (U.S. & The Netherlands), Ken Ducatel (EC, Spain & UK), Patrick van der Duin (The Netherlands), Luke Georgehiou (UK), Theodore Gordon (U.S.), Harold Linstone (U.S.), Vincent Marchau (The Netherlands), Gilda Massari (Brazil), Ian Miles (UK), Mary Mogee (U.S.), Ahti Salo (Finland), Fabiana Scapolo (EC, Spain & Italy), Ruud Smits (The Netherlands), and Wil Thissen (The Netherlands).

- Technology assessment, and forms of impact assessment, including strategic environmental assessment (anticipating the unintended, indirect, and delayed effects of technological changes)
- Technology foresight, also national and regional foresight (effecting development strategy, often involving participatory mechanisms)

Many of these forms of forecasting use similar tools to accomplish similar ends. But there is a general tendency in government to use phrases that separate thought from action, such as “assessment” and “foresight,” while in industry there is a tendency to use phrases that link thought and action, such as “roadmapping” and “competitive technological intelligence.” There are cross-national differences as well, propelled by differences of societal expectations from markets and governments. Industrial roadmapping, a largely private sector led initiative, originated and became prevalent in the United States, while foresight, a government sponsored activity, became the preferred alternative in Europe. These forms of forecasting—national technology foresight, roadmapping, and competitive technological intelligence—came into prominence at different times, and with relatively little effort to clarify their similarities and differences.

TF usually focuses on specific technologies, but sometimes the scope is more encompassing. A firm might roadmap a set of related technologies and products; an industry association might roadmap the gamut of emerging technologies potentially affecting its sector; or a nation could roadmap technologies across its economic base. For example, a U.S. semiconductor industry association roadmap, regularly updated to support industry planning, had as its early objective regaining global market share in semiconductors. If semiconductor technologies were addressed in a national foresight study, the scope might also include the needs and capabilities of the relevant sciences at the input end, and the possible societal costs and benefits at the outcome end.

Methodologically, both national foresight studies and roadmapping usually bring together people representing different expertise and interests, and use instruments and procedures that allow participants to simultaneously adopt a micro view of their own disciplines and a systems view of overriding or shared objectives [3].

1.3. TREND IN FTA PUBLICATION

How much FTA research publication is out there? In 2006, Alan Ported prepared a literature profile of The FTA domain helping to characterize the growing body of FTA knowledge [4], [31]. Figure 1 is from this study, showing articles relating to FTA appearing in Web of Science. From 1996 through 2003, this is essentially flat – at a modest level of about 100 articles per year, and the study yielded 1018 FTA-related papers for 1996-2006. [This reflects the scholarly literature; it does not capture foresight reports, etc.] Since 2004, activity seems to be increasing. “Trend analysis” is somewhat encouraging for FTA.

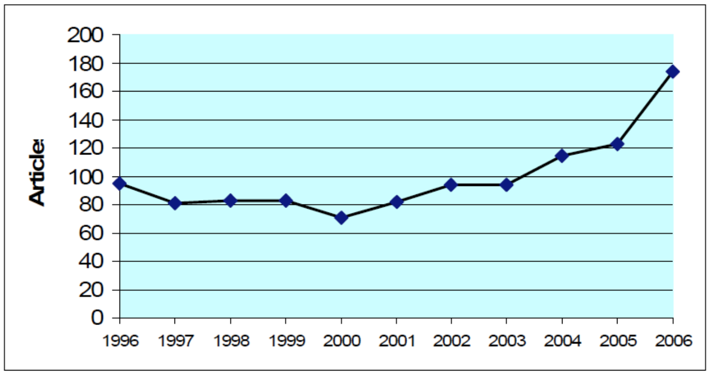

Figure 1: Articles relating to Future-oriented Technology Analysis appearing in Web of Science [31].

The study also examines the sectoral mix of these FTA-generating institutions. Applying a thesaurus that combines certain standard phrasing (e.g., "Univ" as university; "Ltd" or "Corp" as industry), and not trying to capture every one of the originally listed 799 organizations, results in Table 1. Note that the second grouping consolidates several difficult to distinguish types – governmental and non-governmental organizations, and other such institutes. Not surprisingly, publication of FTA articles is strongly led by the academic community (which has the greatest stake in such publication), but note the substantial participation by government and industry.

Type	**# of Articles**	**# of Authorships**	**% of Articles**
Academic	567	779	58%
Gov't/NGO's/Institutes	174	210	18%
Industry	109	142	11%

Table 1: Leading Authoring Organizations by Sector [31]

Where is FTA work being published? Alan Porter's study lists 11 journals with 10 or more publications, where "TF&SC" is the leader, with strong representation of leading technology management journals (Table 2). The "Journal of Cleaner Production" focuses on sustainable development, while "Solid State Technology" shows a number of technology roadmapping articles.

Leading FTA Journals
Journal (# of Articles)
Technological Forecasting & Social Change (114)
International Journal of Technology Management (52)
Futures (49)
Research--Technology Management (26)
Abstracts of Papers, American Chemical Society (14)
Technovation (13)
Journal of Cleaner Production (12)
Journal of Forecasting (12)
R & D Management (11)
Solid State Technology (11)
Technology Analysis & Strategic Management (11)

Table 2: Leading FTA Journals [31]

1.4. TF AND ACCESS TO INFORMATION

Forecasters have long had complex algorithmic approaches at their disposal, but their ability to effectively execute those approaches has been limited by the availability of information and costs of manual information manipulation and analysis.

A defining characteristic of the ‘‘information economy’’ has been the tremendously enhanced access to information. This offers particular promise to improve TF. There are many web sites that provide useful information, including projects, research opportunities, publications, citations, and patents.

Tremendous research and development activity, worldwide, results in explosive growth in the amount of scientific and engineering literature. For instance, Science Citation Index contains almost 15 million abstracts of journal and conference papers published since 1987. US, Japanese, and European patents are searchable online [4] Importantly, many organizations license diverse R&D databases for unlimited searching, e.g., universities for their students and faculty.

2. TF METHODS

2.1 FAMILIES of TF METHODS

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:

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 and Intelligence Methods**
    - Monitoring [environmental scanning, technology watch]
    - Bibliometrics [research profiling; patent analysis, text mining]
4) **Statistical Methods**
    - Correlation Analysis
    - Demographics
    - Cross Impact Analysis
    - Risk Analysis
    - Bibliometrics [research profiling; patent analysis, text mining]
5) **Modeling and Simulation**
    - Agent Modeling
    - Cross Impact Analysis
    - Sustainability Analysis [life cycle analysis]
    - Causal Models
    - Diffusion Modeling
    - Complex Adaptive System Modeling (CAS) [Chaos]

- Systems Simulation [System Dynamics, KSIM]
- Technological Substitution
- Scenario-simulation [gaming; interactive scenarios]
- Economic base modeling [input-output analysis]
- Technology Assessment

6) Scenarios

- Scenarios [scenarios with consistency checks; scenario management]
- Scenario-simulation [gaming; interactive scenarios]
- Field Anomaly Relaxation Method [FAR]

7) Valuing/Decision/Economics Methods

- Relevance Trees [futures wheel]
- Action [options] Analysis
- Cost-benefit analysis
- Decision anaysis [utility analyses]
- Economic base modeling [input-output analysis]

8) Descriptive and Matrices Methods

- Analogies
- Backcasting
- Checklist for Impact Identification
- Innovation System Modeling
- Institutional Analysis
- Mitigation Analysis
- Morphological Analysis
- Roadmapping [product-technology rodmapping]
- Social Impact Assessment
- Multiple perspectives assessment
- Organizational analysis
- Requirements Analysis [needs analysis]

9) Creativity

- Brainstorming [brainwriting; nominal group process (NGP)]
- Creativity Workshops [future workshops]
- TRIZ
- Vision Generation
- Science Fiction Analysis

We will briefly review some of the most popular methods in each category. Note that some of the methods fit into more than one family. For example, bibliometrics – which is a major focus of the MIT/MIST project – is listed under both Statistical and Monitoring/Intelligence Methods.

2.1.1 EXPERT OPINION

Expert Opinion methods include forecasting or understanding technological development via intensive consultation with subject matter experts. The most popular method in this family is the Delphi Method. This method combines expert opinions concerning the likelihood of realizing the proposed technology as well as expert opinions concerning the expected development time into a single position. In Delphi, a sequence of individual interrogations is followed by information and opinion feedback derived from analyzing the initial response data. This feedback, which includes the reasoning and/or justification behind each individual expert's forecast, allows the other experts to revise their forecast in light of the new information. A single acceptable forecast is typically agreed upon after several rounds of this process [6]. Delphi, being the most widely used technique, has been subjected to scrutiny by many authors. Woundenberg [7] has discussed the accuracy and reliability aspects of Delphi. His conclusions are based on the work of many other researchers like Campbell [8], Pfeiffer [9], Dalkey [10], Dalky and Helmer [11], Farquhar [12], Gustafson et al. [13], Parente et al. [14], Hill and Fowles [15] and Martino [16].

2.1.2. TREND ANALYSIS

Trend analysis involves prediction via the continuation of quantitative historical data into the future. Trend analysis is a broad term that encompasses economic forecasting models and techniques such as regression, exponential smoothing and Box-Jenkins' ARINA model and growth curve fitting [6]. A technology usually has a life cycle composed of several distinct stages. The stages typically include an initial adoption stage, a growth stage, a maturity stage and a declining final stage. Growth curve forecasting is based on the parameter estimation of a technology's life cycle curve. The growth curve forecasting method is helpful in estimating the upper limit of the level of technology growth or decline at each stage of the life cycle. This method of forecasting is also helpful in predicting when the technology will reach a particular life cycle stage.

One type of growth curve forecasting method is the Fisher-Pry Analysis. It is a mathematical technique used to project the rate of market adoption of technically superior new technologies and, when appropriate, to project the loss of market share by old technologies [17]. The technique is based on the fact that the adoption of such new technologies normally follows a pattern known by mathematicians as the "Logistic Curve." This adoption pattern is defined by two parameters. One of these parameters determines the time at which adoption begins, and the other determines the rate at which adoption will occur. These parameters can be determined from early adoption data, and the resulting pattern can be used to project the time at which market takeover will reach any given level. Results produced by this technique are highly quantitative. The technique is used to make forecasts such as how the installed base of telecommunications equipment will change over time, how rapidly a new chemical production process will be adopted, and the rate at which digital measuring devices will replace analog devices in petroleum refineries, etc.

2.1.3 MONITORING AND INTELLIGENCE METHODS

Monitoring and its variations, Environmental Scanning and Technology Watch, are suitable for making one aware of changes on the horizon that could impact the penetration or acceptance of the technologies in the marketplace [18]. Reference [1] states “environmental scanning can be thought of as the central input to futures research.” However, the output is too general to support a specific decision. “…The objective of a monitoring system is simply to find early indications of possibly important future developments to gain as much leadtime as possible” [1].

Resource availability is one of the scoping issues associated with these methods since a number of the scanning approaches require the use of experts. Expert panels are created to look out for changes on the horizon that could be important to implement or accomplish plans. Experts are also tracked in a “scan the scanners” manner. TF analysts identify the experts in a field and keep track of those individuals by making occasional contact with them, observing them at conferences or searching the Internet for insights they may have posted.

2.1.4 STATISTICAL METHODS

In the Statistical Methods family, the most popular methods are Correlation Analysis and Bibliometrics. Correlation analysis forecasts the development patterns of a new technology when the development patterns of the new technology are similar to those of existing technologies. Use of this method presupposes that data regarding the development patterns of the existing technologies are available [18].

In 1983, when Martino published [19], there was a correlation between the total installed steam turbine capacity in the United States and the maximum size of a single steam turbine electric generator. This would allow one to forecast the largest size of a steam turbine electric generator based on the forecast total industry capacity.

Many new or potential tools, currently used in future studies, have resulted from advances in information technology and information science. Among them, stand out scientometrics and bibliometrics, tools used traditionally by the information science experts to measure scientific productivity and to identify science and technology networks [20].

According to Porter and Cunningham [21], "social scientists have applied methods of content analysis for decades. Counting scientific publication activity dates back at least to the pioneering work of Derek de Solla Price (1963)… With the advent of electronic text sources and analytical software, content analysis has matured into text mining… Data mining seeks to extract useful information from any form of data, but common usage emphasizes numeric data analysis…Text data mining or text mining exploits text sources of various sorts".

One of the most important aspects of bibliometric analysis is that it goes beyond the experts' biases, allowing the discovery of new facts and patterns that sometimes are not perceived due to the limit of knowledge or prejudiced visions. Some authors point out certain limitations of bibliometric analysis [22,23], considering that not all R&D activities are published or patented: much of the activity of technological development is not included either in journals, conferences, papers or patents in a timely fashion; the counting of publications does not distinguish the quality from its content; each institution has its own patenting policy; and there is no perfect system of classification and indexation of publications.

Besides these limitations, there are essential points for obtaining good results in text mining [20]:

- **Knowledge of the subject under study**: it is important to have a good knowledge of the subject to define the search strategy in databases and analyze its results.
- **Knowledge of the databases to be used**: to know their contents and their structure, their level of standardization and the existing possibilities of data recovery are factors that define the success or failure of the task. The lack of standardization, for example, sometimes makes good text mining impossible due to low trustworthiness of the data.
- **Knowledge of patent information**: if patents are under study, it is important to know about the patents information structure, since they have rules of their own. Patent is a wide field, where techniques, products, applications and legal considerations are strongly mixed. This is also a field most of the time dedicated to industry people and, for example, the academic community does not cite patents very much. Nevertheless, patents are a unique source of information since most of the data and information published in patents are not published elsewhere.
- **Definition of search strategy**: it is an essential step and it is linked to the three previous ones, that is: knowledge of the subject and knowledge of databases and patents. The use of restricted or extremely ample terms, for example, can lead to results that induce to errors of evaluation.
- **Usage of analytical tools**: it is important to have good text mining softwares and also to really know how to use them. Some commercial databases are beginning to provide analytical tools together with the search facilities, but they still have limited possibilities.
- **Results analysis**: experts must analyze the results trying to extract the best interpretation of the histograms, matrices and networks looking for strategic information.

The usage of text mining techniques must, necessarily, involve the experience of information professionals and of domain experts to be successful. The knowledge of information professionals on the available information sources, their contents and structure, and the opinion of experts to define the search strategy and to interpret the results are crucial for the quality of the final work.

2.1.5 MODELING AND SIMULATION

A model is a simplified representation of the structure dynamics of some part of the "real" world. Models can exhibit future behavior of complex systems simply by isolating important system aspects from unessential detail. Modeling requires a good understanding of interactions between these forecasts and the underlying variables or determinants.

One example in this family is Agent Modeling. An agent model involves the creation of computer generated "agents" that "populate" a computer screen, and interact with one another according to a set of behavioral rules [24]. The agents may be of different species; that is, they may have different attributes and may be assigned different rules. Their interaction over time is usually simulated by successive "plays" of the rules as the evolving attributes and spatial positions of the agents are computed. The spaces in the environment in which the agents are placed may also contain rules.

Reference [24] describes an agent model that simulates the spread of an infection in a population, but explains that the model could be used to simulate any attribute that is passed from one person to others in society, such as a disease, an idea or belief, a fad, a market or a behavioral pattern. Using the model provided in the paper as a starting point, [18] claims it may be possible to apply this concept to simulate the growth of use of sustainable energy technologies if each sustainable energy technology is modeled as an agent, such as: clean coal technology, tidal power and photovoltaics, etc. Each agent would have its own attributes and be governed by different rules. For example, an attribute of clean coal may be that it has a negative connotation while an attribute of photovoltaics may bet that it has a positive connotation while that of tidal power has a neutral connotation. Assuming that one set up the spaces to be in some way representative of society; filled with experts, private companies, "the public", government, etc., rules could be set up such that, for example, if a clean coal technology agent met a public space, the rule could require that the infection is retarded. However, if a clean coal technology agent met an expert space, the rule could require that the infection is advanced.

Systems Simulation is another popular method in this family. The major benefit of Systems Simulation is to "allow users to search for the best approaches to an opportunity, facing a challenge, or solving a problem, without the risk or price of costly mistakes" [1]. Given this benefit, it is possible to imagine configuring a system which contains all (or as many as reasonably possible) sustainable energy technologies and running a simulation to determine which technology will have the highest future value [18]. However, although it is possible to imagine this model theoretically, the practical aspects of implementing such a model would be daunting because the accuracy of the pictures that system simulations create depends entirely on the quality of the data and on the realism of the way the relationships are expressed in the model. "To be fully realistic, a simulation-game must have participants free to choose any of the possible alternatives, regardless of the selection at the preceding decision point. If five or more choices are possible at every decision point, it does not take long before the branches of the decision tree number in the hundreds of thousands" [1].

2.1.6 SCENARIOS

Scenario writing proposes different conceptions of future technology. Each conception of the characteristics of the future technology is based on a well-defined set of assumptions. A scenario represents alternative characteristics of the future technology, with each alternative being based on certain assumptions and conditions. The forecaster evaluates the validity of the assumptions. The results of this evaluation are used to determine the scenario most likely to occur [6].

2.1.7 VALUING/DECISION/ECONOMICS METHODS

The most popular method in this category is the "relevance tree approach". This is a normative approach to TF. The goals and objectives of a proposed technology are broken down into lower level goals and objectives in a tree-like format. In this way, the hierarchical structure of the technological development is identified. The probabilities of achieving the goals and objectives at the various levels of technological development must be estimated. The probabilities can then be used to forecast the likelihood of achieving the stated goals and objectives of the proposed technology [6].

2.1.8 DESCRIPTIVE AND MATRICES METHODS

A growing activity in this category is technology roadmapping, which projects major technological elements of product design and manufacturing together with strategies for reaching desirable milestones efficiently. Roadmaps typically run several technology or product generations (e.g., 2 to 10 years) ahead. In its broadest context, a science and technology roadmap provides a consensus view or vision of the future science and technology landscape available to decision makers. Thus, the predictive element emphasized in early TF is supplemented with a normative element, that is, however, narrower, more targeted, and more directly actionable than is the normative element implicit in TA. In the past, the institutional champions for roadmapping were mainly military industrial organizations; more recently, they have been other large corporations and industry associations [2].

Analogies are also widely popular descriptive methods. The use of Analogies in forecasting involves a systematic comparison of the technology to be forecast with some earlier technology that is believed to have been similar in all or most important respects. According to Martino in [19], one of the shortcomings with analogies is that they "…are based on the assumption that there is a 'normal' way for people to behave and that given similar situations, they will act in similar ways. However, there is no guarantee that people today will act as people did in the model situation. Hence the forecast is at most probable, never certain".

2.2. HOW TO EVALUATE THE QUALITY OF TF METHODS?

Evaluation of TF methods is quite challenging. Evaluation should establish, as far as possible, how far an activity has achieved—or how far it appears to be achieving—its intended outcomes. Yet, here is no general-purpose toolkit for evaluating TF studies' influence and outcomes. A key challenge is establishing where a TF process begins and ends. Also, determining the extent to which an activity would have taken place without the intervention of the TF is problematic.

The Technology Futures Analysis Methods Working Group (TFAMWG) [3] gives a brief study that focuses on the evaluation of national Tech Foresight programs.[2] They choose Tech Foresight,

---

[2] Technology foresight is a term used for national TF activities in general. [30] states that much of the pioneering work in technology foresight in the industry and at national level was done in the USA. Large think tanks, such as Rand and Hudson, made many technological forecasts since 1960s. The studies basically intended to help large corporations and government agencies to adjust their technological

as it has a mission of informing specific decisions. Tech Foresight also seeks to enlarge excessively short-term horizons and facilitate the formation of new networks around technologically and socially innovative activities.

TFAMWG [3] draws attention to two aspects of evaluation: product and process:

Product-oriented work results, for example, in priority lists, reports arguing the case for a strategy in a particular field of science and technology (S&T), proposals for reform of educational systems, etc. It is possible to count and document products (reports, web pages, etc.), to examine their diffusion (readership, citations, etc.), and even to get some estimate of their use.

Process-oriented work results in network building, shared understanding, the formation of new alliances, bringing new participants into the innovation policy debate, etc. These consequences are harder to measure and monitor and will typically require more explicit examination - they will rarely be available as by-product data from the administration of a program.

TFAMWG [3] examines evaluation and use of Tech Foresight in terms of:

Futures: If accuracy is an issue, the assessment depends on the period that Tech Foresight addressed. In a short horizon (say, 5 years) critical technology exercise, this is not too serious a delay. But when Tech Foresight involves a time scale of 15 or more years, assessment is difficult—and its utility more problematic.

Participation and Networks: Examination of many aspects of the engagement of people in the Tech Foresight process and of the formation and consolidation of networks is best carried out in real time—memories get hazy rapidly and many of these activities go unrecorded. But many of the outputs and outcomes of such activities will take time to mature and require ex post investigation.

Action: A major question here is that of attribution. [3] claims that actions are often packaged as resulting from Tech Foresight, while in reality the decision makers use the reference to the study merely as a means of legitimation. Similarly, many actions may be taken that have their origins in the study but are not attributed to that source.

2.3. 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

investment. Since the early 1970s, various ministries and agencies in Japan have been conducting repeated technological foresight studies (among them the Ministry of Trade and Industry (MITI) , Economic Planning Agency (EPA) and the Science and Technology Agency (STA)). Western European countries followed with systematic technology foresight activities in the 1990s [12].

existing technologies, a reasonable choice is a method based on information obtained from a panel of experts (i.e., Delphi method or interviews). Given a moderate to large amount of medium to high validity data and a high degree of similarity between proposed technology and existing technologies, they propose using correlation analysis. When there is medium or large amount of high validity data, trend analysis is the most appropriate method.

A more recent study [25] 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.

An important element of the MIT/Masdar TFDMS project is bibliometric analysis. 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.

Many articles state that, because of the complexity of TF and because each forecasting method can deal with only limited aspects of a forecasting case, it is often advantageous to use several different forecasting methods simultaneously. In line with this, the MIT/MIST TFDMS research project extends and improves “tech-mining” techniques and introduces semantic enabled features. Our analysis will be evaluated via consultation with domain experts and stakeholders and the performance of programs and tools will be tested and fine-tuned with case studies on renewable energy and sustainability.

3. TF IN PRACTICE

How are corporate decisions, such as investing millions of dollars to a new technology like solar energy, being made? Are funding allocation decisions based on “objective, repeatable, and quantifiable” decision parameters? As Jerome C. Glenn, the director of the Millennium Project indicates in his reply to the abovementioned questions, “Corporations tend not to share that information.” Alan Porter, a leading figure in TF, states that “These decisions are most often based on "tacit knowledge" without much systematic TF or competitive technical intelligence (CTI) being utilized.” The literature on TF in practice concentrates upon national exercises and documents the various national programs and approaches. In contrast, this statement is not true for TF in companies.

As the focus of this part is on companies using TF tools for their future investments and resource allocations, the term technology intelligence (TI) will be used interchangeably with TF; as TI, CTI, and “competitive technical intelligence” are more popular in the corporate world than the term TF.

To show the evolution of TF in companies, let's start with the results of a 1978 survey undertaken to estimate the extent of use of TF in U.S. industry [26]. For this survey, a detailed questionnaire was responded by 103 companies most of which belong to Fortune 500. The respondent firms came in all sizes-the sales of these firms ranged from $40 million-$55 billion.

At that time, as many as 80% of the firms responding to the survey performed formal TF. Results indicate that as many as one out of five responding firms perform TF regularly (once every six months). The number of firms perceiving TF as crucial to their business was 7% of the respondents. A large 42% felt TF is important right now, and an additional 10% (for a total of 52%) felt that TF will be important in the next five years. The use of TF for long-range decisions at any executive level seemed to be rare (less than 2%). TF was not perceived by top-level line executives to be of much use in long-range applications (over eight years), mainly because of the greater concern of these individuals towards short-term market trends. [26] concludes that, according to this sample, a firm that feels TF is crucial to its operations typically has a high technology operation; its manufacturing is moderately capital intensive; it also emphasizes R&D and commits a reasonable portion of its R&D budget to basic research.

In the last few years, a strong interest in systematic TI can be detected in many technology-intensive large companies [27]. Novartis' TI approach on the corporate level is a good example [28]. Novartis used 180 globally distributed participants, among them specific teams, informal discussion groups and several fulltime technology intelligence specialists, to communicate during the year via intranet, where new trends are discussed. Furthermore, three to four times a year they meet physically in order to integrate the information gathered into a holistic and shared picture and in order to create an atmosphere of trust with their colleagues. This process somewhat resembles IBM's Horizon Watch.

One other good example comes from GlaxoSmithKline [29]: Just after the merger of SmithKline & French with Beecham (1990), the new corporate senior management asked how best to reallocate the combined $1 billion R&D budget. A team from R&D and central marketing was assembled to look at the company's existing portfolio of therapeutic area research to assess the viability of each and to explore new areas of unmet medical conditions or needs that could be profitably explored. A consulting firm, which had also been called upon, proposed locating the various therapeutic areas within a typical positional map of commercial attractiveness vs. technical feasibility or strength (Figure 2, left). The firm was unwilling to recommend the discontinuation of work in any one of the therapeutic areas

The head of R&D, however, was not satisfied, and asked the small, four-person intelligence group in the R&D section to look at another tool to guide the company in refocusing its R&D resources. That led to the application of scientometrics[3] or science mapping, a technique of using computer algorithms to identify connection patterns within the recently published scientific literature. Based on these patterns, a structural map of the scientific community can be created, showing the interrelationships between disciplines and the distribution of research communities. A scientometric or knowledge map can identify the structure of a particular area of scientific research and measure its performance: How "hot" is this research area? How quickly are new

[3] Scientometrics is concerned with the quantitative features and characteristics of science. Emphasis is placed on investigations in which the development and mechanism of science are studied by statistical mathematical methods. In practice, as in the SmithKline Beecham case, scientometrics is often done by measurement of (scientific) publications using bibliometrics. For purposes of this report, scientometrics and bibliometrics are used interchangeably.

discoveries being made? Is the field growing, or imploding upon itself? Maps can be drawn for each level in the hierarchy and color-coded according to performance measures.
SmithKline Beecham used this technique as one element in the redirection of its R&D resources. After generating scientometric maps of the seven research-based universes (or therapeutic areas) in which the merged company was active, they concluded that the field of gastrointestinal disease (GI) research in particular was not generating a significant amount of high-performance research. The positional map was redrawn (Figure 2, right). The company decided to close its research activities in this area, and to focus on research in the remaining six: the central nervous system (CNS), inflammatory disorders (INF), cardiorespiratory disorders (RD), metabolic disease (MD), cardiovascular disease (CV) and anti-infection agents (AI). The company then turned its attention to research platform (technology) areas, identifying networks of research communities common to the seven therapeutic areas. One such network constituted a technology universe working in the broad area of genomics, an interesting but uncertain field in the early 1990s.

Through scientometrics, it identified several university groups and small companies that were conducting high-momentum research in the area. Further investigation of these high-momentum groups led to the first genomics agreement in the industry between SmithKline Beecham and Human Genome Sciences. Scientometrics also helped SmithKline Beecham to locate a multimillion-dollar research facility focusing on the central nervous system. Maps showed that centers of excellence in CNS research were located on the east and west coasts of the U.S. and in France, which was where the company ultimately built one of its research satellites. In short, scientometric technology gave the company an important intelligence perspective that enabled it to reshape its research portfolio for greater productivity, and to define a number of promising technology opportunities.

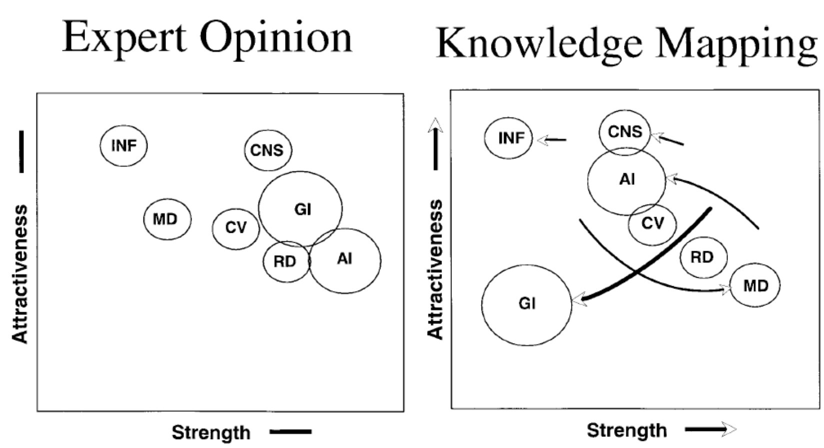

Figure 2: The map (left) of commercial attractiveness vs. technical strength for seven therapeutic areas—the central nervous system (CNS), inflammatory disorders (INF), cardiorespiratory disorders (RD), metabolic disease (MD), cardiovascular disease (CV), gastrointestinal disease (GI), and anti-infection agents (AI)—was redrawn based on the use of scientometrics (right). GI was then dropped from the R&D program [29].

In a recent study by [28], a total of 147 interviews were performed, in 26 technology intensive large companies in Europe and North America (Table 3). Interviewed were specialists of the technology intelligence units and the technology acquisition intelligence units, as well as customers of these intelligence units from top management including in each case: the head of research or the CTO (chief technology officer), a member of middle management and a few individual researchers. Companies from the pharmaceutical, telecommunication equipment and automotive/machinery industries were examined with the goal of exploring industry differences in the management of technology intelligence processes.

	Pharmaceuticals	Telecommunications equipment	Automobile/Machinery	Total
Europe	Novartis Roche Bayer Zeneca Boehringer Ingelheim Hoechst Marion Roussel	Nokia Ascom Siemens Swisscom Philipps	Sulzer DaimlerChrysler Hilti Schindler Landis & Gyr Bosch	17
USA	Pfizer Merck Glaxo Wellcome[1] SmithKline Beecham DuPont	Lucent Technologies Nortel Networks Cisco	Ford	9
Total	11	8	7	26

Table 3: The companies included in "Technology Intelligence Processes in Leading European and North American Multinationals." study [28]

According to this study, the selection of the TF methods in a company is not only influenced by the objective of individual or organizational learning sought or by the time horizon of planning but also by the industry. Table 4 shows the intensity of use of different information sources in the industries studied.

	Pharmaceuticals	Electronics	Auto/Machinery
Publication frequency analyses	• • •	• •	•
Publication citation analyses	• • •	–	–
Quantitative conference analyses	• •	• • •	•
Patent frequency analyses	• •	• • •	• • •
Patent citation analyses	–	–	•
S-curve analyses	–	–	–
Benchmarking studies	• • •	• • •	• • •
Portfolios	• • •	• • •	• • •
Delphi studies	–	–	–
Expert panels	• • •	•	• •
Flexible expert interviews	• • •	• • •	• • •
Technology roadmaps	• •	• • •	–
Product technology roadmaps	–	• • •	•
Product roadmaps	• • •	–	–
Experience curves	•	• • •	• •
Simulations	• •	–	–
Option pricing models	• •	–	–
Scenario analyses	• • •	• • •	• • •
Lead user analyses	–	• • •	• •
Quality function deployment	–	• •	• • •

• • • = often used • • = sometimes used • = rarely used – = not used

Table 4: Intensity of use of different information sources in the industries studied [28].

Table 4 shows that commonly used bibliometric indicators that are important elements of the MIT/MIST TFDMS project (such as publication frequency, publication citation, quantitative conference, patent frequency and patent citation analyses) are being intensely used for TF in several industries. For example, the pharmaceutical industry uses publication citation and frequency analyses, the telecommunications equipment industry focuses on patent frequency analyses and quantitative monitoring of conferences, and the automobile and machinery industries use patent citation and frequency analyses. The MIT/MIST TFDMS research project focuses on alternative energy research as an initial focal area of demonstration. Although none of the three industries mentioned in Table 4 are identical to the alternative energy industry, pharmaceuticals and telecommunications seem to be close because of the importance of new scientific results and monitoring of the techno-economic changes in these industries.

The pharmaceutical industry is a science-driven industry. Starting from fixed customer needs, which can be determined in the form of long-term epidemiological studies, the scientific environment is scanned for most promising innovations. New scientific research results are often of high competitive relevance and are immediately used. Publication citation analyses are therefore often used in the pharmaceutical industry. This explains the better applicability of publication citation analyses in the pharmaceutical industry compared to the telecommunications and automobile industries, in which scientific advances are of less competitive importance.

Many pharmaceutical companies combine publication citation analyses with ideal products from the marketing point of view. Ideal targets are identified in an iterative process. As the projects move forward in the product pipeline, techno-economic, time and competitive aspects especially start to dominate assessments. Quantitative assessments are increasingly used. Pharmaceutical companies try to handle the technological uncertainty and the high failure rate of R&D projects by using options pricing methods. The large R&D budgets and the rising pressure to increase effectivity in the selection of R&D projects are the root cause of the use of expensive and complex methods, such as simulations and publication citation analyses.

On the other hand, the telecommunications equipment industry is a market-driven industry. Technological progress and market development are closely coupled. This is reflected by the importance of lead user analyses, technology product roadmaps and scenario analyses. The integrated technology and market planning is seen as necessary because of the high rate of technological and market change. In the automotive industry in contrast, there is a slow rate of technological and market change.

In the telecommunications equipment industry, normally several technologies compete to become a standard and often imply different markets. At the same time, these technologies are only unstable dominant designs, which are substituted after a comparably short time. Besides the identification of innovation impulses from science, monitoring of the changing techno-economic importance in order to select the right technology and the right time to invest in a technology is of great importance. The importance of the monitoring of the techno-economic changes is mirrored by the intensive use of quantitative monitoring of conferences, experience curves and patent frequency analyses. Publication citation analyses and patent citation analyses are not used because scientific advances often take many years to become competitively relevant and the rate of change is too fast.

The automobile and machinery industries are more mature and less dynamic industries than the pharmaceutical and telecommunications equipment industries. Technological as well as market uncertainty are comparably low. The main focus is the integration of customer needs in products and incremental innovations. Radical innovations are mainly triggered by the regulatory environment. Very often, therefore, scenario analyses, quality function deployment and lead user analyses are used. Changes in the scientific environment are perceived to be of less competitive importance compared to in the telecommunications equipment and pharmaceutical industries. Patent citation analyses are mainly used to scan for new technologies.

According to [28], the longer the time horizons, the more the companies studied try not to forecast the development of a technology as precisely as possible, but rather tend to determine a commonly shared and supported, partly normative future starting from an intensive analysis of the environment.

In a 2001 study, Reger[30] made interviews in 25 multinational companies.[4] More than half the firms investigated emphasized that TI is an unstructured and unsystematic process – which illustrates the opportunity for improvement. The interviews show that the companies investigated use numerous different methods/tools for technology foresight with different intensity. Nearly every company uses patent and publication analyses, market analyses, benchmarking and competition analyses, scenarios, creativity techniques, technology roadmaps, internal or external workshops or Internet search agents/machines

CONCLUSION

Analysis of emerging technologies and identification of technologies with the greatest potential using technological forecasting (TF), informs critical decisions ranging from the individual organization to the multinational level. As a part of MIT/MIST research on "Technological Forecasting using Data Mining and Semantics" (TFDMS), this report briefly summarizes the field of TF, its techniques and applications.

There has been little systematic attention to the conceptual development of the TF field as a whole. Therefore, we address many overlapping forms of forecasting technology developments and their impacts, including technology intelligence, forecasting, roadmapping, assessment, and foresight in our report. The literature profile of the TF field in general shows increasing research activity and interest in TF as the need for TF increases.

There are hundreds of methods being used for TF. Our report gives a brief summary of the families of TF methods. Many experts in the field agree that it is advantageous to use several methods simultaneously, as each method can only deal with limited aspects of a forecasting case. In line with this, our TFDMS research extends and improves "tech-mining" techniques and introduces semantic enabled features, which should improve results by enhancing information retrieval and mediating contextual incompatibilities. Our analysis will be evaluated via consultation with domain experts and stakeholders and the performance of programs and tools will be tested and fine-tuned with case studies on renewable energy and sustainability.

The quality of forecasts greatly depends on proper selection and application of appropriate method. For example, [21] states that taking the opinion of experts for interpreting the results is

[4] Fifteen of the companies interviewed were in the fields of computers, electronics, energy, or aviation, and four companies in the automobile industry. The telecommunication/network operators sector was represented by four companies and the chemical industry by three. Sixteen of the corporations in the survey have their headquarters in Western Europe, five in Japan and five in the United States. The following persons were interviewed within the companies:
- The head of technology foresight, or those responsible for technology foresight processes,
- Heads of the technology planning/technology strategy group or department,
- Customers' such as, e. g. the head of an R&D/technology centre or the head of corporate research, the head of technology development in a business field or a member of a strategic committee.

Most interviews were conducted with senior managers responsible for the technology foresight process or for corporate R&D/technology strategy. All companies interviewed described their competitive environment as highly dynamic. The budget for research and development (R&D) in the interviewed firms was between 80 million and 4. 5 billion Euro.

crucial for the quality of the final work in tech mining. Although TF experts agree that the application demands that the technique used need to be time-, space- and technology-specific, there is little research done on matching the TF methods techniques to a particular technology.

Some of the commonly used bibliometric indicators which are important elements of the MIT/MIST TFDMS project (such as publication frequency, publication citation, quantitative conference, patent frequency and patent citation analyses) are being used for TF in the industry. Yet, several studies emphasize that TF in practice, especially in companies, is an unstructured and unsystematic process – which illustrates the opportunity for improvement.

Enhanced access to information offers particular promise to improve TF. In an era when tremendous research and development activity worldwide results in explosive growth in the amount of scientific and engineering literature, The MIT/MIST research on developing novel methods for automatically mining science and technology information sources will contribute to this improvement.

REFERENCES

[1] S. Madnick, W.L. Woon, Technology Forecasting Using Data Mining and Semantics, MIT/MIST Collaborative Research, 2008-2009.

[2] V. Coates, M. Faroque, R. Klavins, K. Lapid, H.A.Linstone, C. Pistorius, A.L. Porter, On the future of technological forecasting, Technol. Forecast. Soc. Change 67 (1) (2001) 1 – 17.

[3] Technology Futures Analysis Methods Working Group, Technology futures analysis: toward integration of the field and new methods, Technol. Forecast. Soc. Change 71 (2004) (3), pp. 287–303.

[4] D. Zhu and A.L. Porter, Automated extraction and visualization of information for technological intelligence and forecasting, Technological Forecasting and Social Change 69 (2002), pp. 495–506.

[5] T.J. Gordon, J.C. Glenn (Eds.), Futures research methodology, Version 2.0 Millennium Project of the American Council for the United Nations University, 2003 July.

[6] Levary, Reuven R, Han, Dongchui. (1995, January). Choosing a technological forecasting method. Industrial Management, 37(1), 14.

[7] F. Woundenberg, An evaluation of Delphi, Technol. Forecast. Soc. Change 40 (1991) 131 – 150.

[8] R. Campbell, A methodological study of the utilization of experts in business forecasting, PhD Dissertation, UCLA, 1966.

[9] J. Pfeiffer, New Look at Education: System Analysis in Our Schools and Colleges, Odyssey, New York, 1968.

[10] N. Dalkey, An experimental study of group opinion: The Delphi method, Futures 1 (1969) 408 – 420.

[11] N. Dalky, O. Helmer, An experimental application of the Delphi method to the use of experts, Manage. Sci. 9 (1963) 458 – 467.

[12] J.A. Farquhar, A Preliminary Inquiry into the Software Estimation Process, Rand, RM-6271-PR, August 1970.

[13] D.H. Gustafson, R.K. Shukla, A. Delbecq, G.W. Walster, A comparative study of differences in subjective likelihood estimates made by individuals, interacting groups, Delphi groups, and nominal groups, Organ. Behav. Hum. Perform. 9 (1973) 280 – 291.

[14] F. Parente, J. Anderson, P. Myers, T. O'Brien, An examination of factors contributing to Delphi accuracy, J. Forecast. 3 (1984) 173 – 182.

[15] K.Q. Hill, J. Fowles, The methodological worth of Delphi forecasting technique, Technol. Forecast. Soc. Change 7 (1975) 179 – 192.

[16] J.P. Martino, The precision of Delphi estimates, Technol. Forecast. 1 (1970) 293 – 299.

[17] A. Sahlo, K. Cuhls, "Technology foresight – past and future", Journal of Forecasting, Vol. 22 (2003) pp.79-82

[18] J.G. Phillips, T.R. Heidrick, I. J. Potter, "Technology Futures Analysis Methodologies for Sustainable Energy Technologies", Technology Management: A Unifying Discipline for Melting the Boundaries (2005) 155-165

[19] J. Martino, Technological Forecasting for Decision Making, 2nd ed. New York, NY: North-Holland, (1983) pp: 39, 40.
[20] M. de Miranda Santo, G. Massari Coelhno, D.M. dos Santos and L. Fellows Filho, Text mining as a valuable tool in foresight exercises: a study on nanotechnology, Technol. Forecast. Soc. Change 73 (2006), pp. 1013–1027.
[21] A.L. Porter and S.W. Cunningham, Tech Mining: Exploiting New Technologies for Competitive Advantage, John Wiley & Sons, Hoboken (New Jersey) (2005).
[22] A.L. Porter and M.J. Detampel, Technology opportunities analysis, Technol. Forecast. Soc. Change 49 (1995), pp. 237–255.
[23] A.L. Porter, Innovation forecasting using bibliometrics, Compet. Intell. Rev. 9 (1998) (4), pp. 11–19.
[24] T.J. Gordon, "A simple agent model of an epidemic," Technological Forecasting & Social Change, vol. 70 (2003) pp. 397-417.
[25] S. Mishra, S.G. Deshmukh and P. Vrat, "Matching technological forecasting technique to a technology", Technol. Forecast. Soc. Change (TFSC) 69 (2002), pp. 1–27
[26] R. Balachandra, Technological forecasting: who does it and how useful is it?, Technological Forecasting and Social Change 16 (1980), pp. 75–85
[27] E. Lichtenthaler, a. Technological change and the technology intelligence process: a case study, J. Eng. Technol. Manag. 21 (4) (2004), pp. 331–348
[28] E. Lichtenthaler, b. Technology Intelligence Processes in Leading European and North American Multinationals. R&D Management 34 (2) (2004) 121–135.
[29] PM Norling, JP Herring, WA Rosenkrans, M Stellpflug, SB Kaufman, "Putting Competitive Technology Intelligence To Work" Research-Technology Management, Vol. 43, No. 5. (2000), pp. 23-28.
[30] G. Reger, (2001) "Technology foresight in companies: from an indicator to a network and process perspective." Technology Analysis & Strategic Management, 13, 4, 533– 553.
[31] A.L. Porter, P. in van der Duin (ed.), Knowing Tomorrow? How Science Deals with the Future, Eburon Academic Publishers, Delft (2007) 183-201