LONG-RUN FORECASTING OF EMERGING TECHNOLOGIES WITH LOGISTIC MODELS AND GROWTH OF KNOWLEDGE

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In this paper applications of logistic S-curve and component logistics are considered in a framework of long-term forecasting of emerging technologies. Several questions and issues are discussed in connection with the presented ways of studying the transition from invention to innovation and further evolution of technologies. First, the features of a simple logistic model are presented and diverse types of competition are discussed. Second, a component logistic model is presented. Third, a hypothesis about the usability of a knowledge growth description and simulation for reliable long-term forecasting is proposed. Some interim empirical results for applying networks of contradictions are given.

Keywords:

component logistic model, innovation process, knowledge acquisition, OTSM-TRIZ

INTRODUCTION

An innovation can be seen as the result of a sequence of a production of knowledge and information along a chain that consists of a concept definition, experimentation for validation of the concept and finally exploitation on the market. The outputs of these activities are knowledge or information. But as the different activities along the chain have different time constants and are not systematically harmonized from a decision point of view, the flow of knowledge between them must be synchronised. In order to do so, the knowledge and information resulting from an activity is often stored.

From a quality management point of view the trends of improvement concern the cost, delay and quality of the process leading to innovation. In order to adapt the time-to-produce and time-to-market to the context of increased competition it becomes necessary to anticipate the production of knowledge so that required knowledge is available at the right time and production resources of the innovation chain are used for producing relevant knowledge.

Our research deals with forecasting problems for the exploration activities (conceptual design stage requiring inventive activities) along the innovation chain. General research in forecasting provides general methods and technologies. Our purpose is to solve the problems that prevent us from using them for forecasting the evolution of the parameters of a technological system even if this system is unknown. In this paper we review and discuss forecasting technologies based on so called logistic models.

ABOUT INNOVATION

Sometimes long-term technological forecasting is perceived as an attempt to predict the technological future. Yet such an attempt would be condemned to failure. Why? Because technologies are embodied in innovations – i.e., products or processes which have successfully passed the barrier of user adoption. Unfortunately for the firm putting innovative products onto the market, some innovative products and processes do not pass this barrier and hence, never become innovations. It is commonly accepted that the future success of an innovative product can hardly be predicted, as it is often the outcome of complex interactions between a set of elements: the product itself, the users (their habits, competences, etc.), the economic environment of the product (competitors and complementary products) as well as its socio-political environment (laws, social concerns, etc.). These elements are continuously evolving themselves – by direct interaction or independently – so that in turn, the success of an innovative product appears to be rather unpredictable.

Even though they belong to quite a general lexicon, the terms we are using should to be explained in detail.

Invention

Invention relates to the transposition of technical and scientific principals into an "artefact" to provide a "new way" to accomplish a (more or less generic) function. In inventions, the barrier of technical feasability has been passed. Yet uncertainties remain: will the product pass the test of standard use? Will it be possible to produce and bring the product to market in a satisfying way? Will the potential buyers eventually adopt the product? These issues are related to a series of uncertainties.

Innovative product or process

A product or a process is innovative if it is "new" for the group of people who are likely to use it.

In the case of an innovative product, uncertainty concerning the industrialization and distribution is partially overcome. This simple definition seems usable but it is obviously relative: a product may be innovative for the group of users it is intended to, but not innovative for another group of users. For instance, a company implementing quality management methods could see that as an innovation, but the innovation is only internal to the firm.

Innovation

An innovation is an innovative product or process that has passed the barrier of user adoption. Innovative products and processes often never become an innovation because they are rejected by the "market". In case of market adoption, it might take quite a long time until the innovation is qualified: the diffusion curve can be slow.

Innovation process

This term refers to the global process going from invention to innovation, i.e., adoption of an innovative product/process by potential uses.

The innovation process consists of uncertainty reduction over a given period. Time *per se* is not really important. What is important in our view is the sequence of activities of the actors taking part in the process. These actors are resource providers for the process: for the firm itself, but also for research laboratories providing outputs of scientific research, suppliers of needed components and networks providing useful collaborations. This means that an innovation process may take a long time if resources are not provided or provided in an unorganized way.

This leads us to an important point: efficient management of the innovation process (from invention to market) requires forecasting of the resources needed and actors involved along the process. Forecasting enables us to identify key resources – i.e., resources that are likely to be unavailable and to hinder the process – and to plan and organize R&D so that key resources are available “on time”.

Long-term forecasting will permit us to anticipate and organize the availability of resources needed for future innovation processes.

RELATED WORK

Our research on long-term technological forecasting is inspired by the description of "the lifeline" of technological systems from Altshuller G.S. [1] where contradiction models, S-curves, and the limitation of resources play important roles.

The distinction between short-, medium-, and long-term forecasts, based on three phases of S-curves is proposed in Figure [2]. A short-term technological forecast is about one phase of an S-curve, while a medium-term forecast considers two phases. The scope of study for a long-term forecast is usually beyond one technology, since it studies at least three phases on an S-curve and may consider several growth processes and more than one system.

Our article presented at the ICED'07 conference [3] depicts some theoretical and practical results from two forecasting projects. The concept of critical-to-X feature is proposed in order to unify qualitative and quantitative studies for long-term forecasting. How the prediction of technological barriers can be supported by mapping the contradictions in combination with the assessment of limiting resources is illustrated in this paper [3] by case studies for energy technologies.

In our paper for the TFC’07 conference [4] emphasis on the definition of growing parameters for a logistic growth model is made. To deal with the issue when there is no data for emerging technologies, the naïve and causal methods for long-term forecasting are used.

In order to distinguish the two principal ways of addressing the problems of long-term technological forecasting we have distinguished two complementary directions: a bypass way through substitution of technologies or a direct way through study the growth of knowledge.

Our paper, developed for TFC’08 refers to a direction through substitution of technologies [5] and discusses some working hypotheses of using the so called naïve methods for long-term forecasting by applying logistic substitution models, proposed by Marchetti C. [6].

In the present paper we are focusing our attention on ‘subsystem’ direction which applies causal methods to foresee new technology diffusion in long-run prospects using knowledge growth as a cause factor of technology change. Some working definitions for the components of knowledge acquisition process are given. Lastly, it is proposed to apply the component logistic models [7, 8] for specifying exploration, experimentation and exploitation phases according to knowledge growth.

In the following section a short history of logistic models, a simple logistic S-curve, the concept of competition, and a component logistic model are presented. The section *Applying Component Logistic Growth for Technological Forecasting* explains the idea for linking growth of knowledge with diffusion of technologies in view of long-term forecasts. The concluding remarks propose directions for future research.

LOGISTIC MODELS AND COMPETITION

The first reference to the logistic equation as a model of population growth can be found in Pierre-Francois Verhulst (1838, 1845, 1847). In 1925 and 1926, working independently Lotka Alfred J. and Volterra Vito generalized the growth equation into a model of competition among different species and coined the predator-prey equations.

Early studies about technological substitution described by S-curves were done in 1957 by Griliches, Z and in 1961 by Mansfield [13]. The diffusion of the innovation theory, formalized by Everett Rodgers [14] in 1962 postulated that innovations spread in society in an S-curve.

A significant achievement was accomplished by Fisher, J.C. and Pry, R.H. (1970) by formulating the model for binary technological substitution as an extension of Mansfield's findings [15]. Marchetti C. proposed the logistic substitution model to describe technology substitution in the dynamics of long-run competition (1976-1979) by extensively using the Fisher-Pry transform [6]. In 1994 Meyer P.S. proposed the component bi-logistic growth model [7]. Later on, a component logistic model with multi-logistics generalizes the bi-logistic growth model [8]. Logistic substitution and component logistic models provide clear and suggestive outputs for supporting medium- and long-term forecasting of technology change [6-8, 16-19]. Logistic models are also widely and successfully used in microeconomics and econometrics for modelling individual decisions [38].

SIMPLE LOGISTIC MODEL

Natural growth of autonomous systems in competition might be described by the logistic equation and the logistic curve respectively. Natural growth is defined as the ability of a 'species' (systems) to multiply inside finite 'niche capacity' (i.e. carrying capacity [7], or physical limit of resources [1]) during a time period.

Provided function parameters can be estimated using a partial set of data (e.g. efficiency of internal combustion engine change over last 20 years). It is possible to use the logistic equation in a predictive mode (e.g. how much efficiency will grow and when). Nevertheless, availability of a reliable dataset is a principal limiting factor for applying the S-curve model to technological forecasting [9, 11].

In order to describe continuous "trajectories" of growth or decline through time in socio-technical systems, one generally applies the three-parameter logistic growth model (1):

$$N(t) = \frac{\kappa}{1 + e^{-\alpha t - \beta}} \qquad (1)$$

Where

N(t) – the number of units in the 'species' or growing variable to study; κ – is the asymptotic *limit of growth*;

α – is the *growth rate* which specifies[1] "width" or "steepness" of the S-curve (e.g., α=0.19 means roughly 19% growth per time fraction); it is frequently replaced with a variable characteristic duration (Δt) that quantifies the time required for the trajectory to grow from 0.1κ to 0.9κ. Characteristic duration Δt is used more than α for the analysis of time-series data since the units are easier to appreciate. The decline can be described by a logistic with a negative Δt.

β – specifies the time (t_m) when the curve reaches 0.5κ: the *midpoint* of the growth trajectory (t_m implies symmetry of simple logistic S-curve).

These three parameters κ, α, and β are usually calculated by fitting the data. There are diverse fitting techniques. For instance, the asymptotic limit of growth κ can be estimated by expert judgment, when α, and β are optimized to minimize residuals.

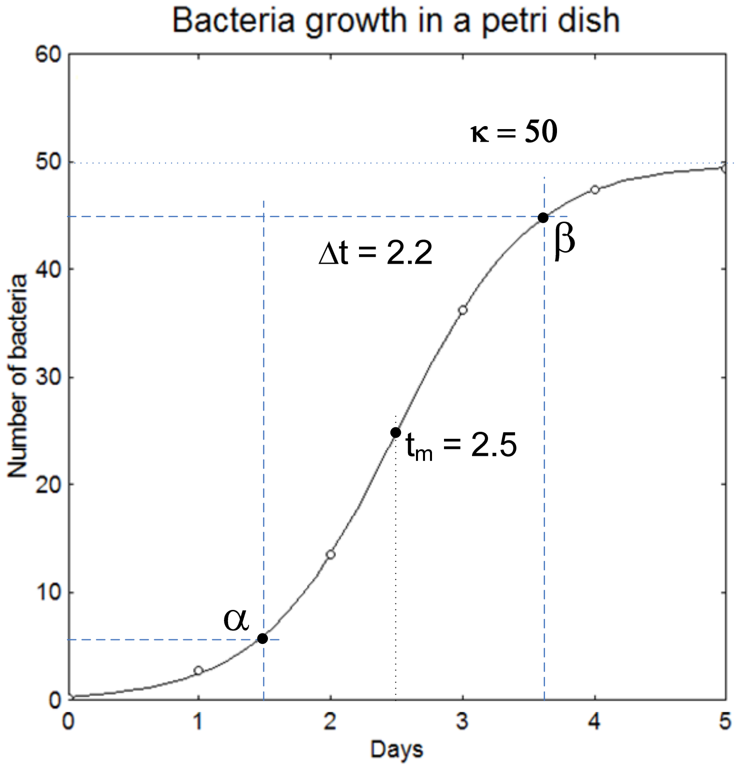

Figure 1: Growth of a bacteria colony consuming sugar and minerals in a closed Petri dish fitted to a logistic curve: limit of growth κ=50 species, characteristic duration Δt=2.2 days, midpoint tm = 2.5 days.

In various publications it was concluded that the other models of non-symmetric growth have limited application due to their complexity and low efficiency for technology forecasting [9-12]. Empirical studies have shown that the S-shaped curve is present in thousands of growth and diffusion processes [3, 6, 16, 18]. Therefore, this model can be applied to both systems where the mechanisms of growth are understood and the growing principles are hidden.

[1] Where *e* - the base of the natural system of logarithms, having a numerical value of approximately 2.71828

Naïve vs. Causal Methods

Naïve methods apply past data about the growing variable (Y) to specify trends and extrapolate them into the future (see Figure 2). Causal methods apply causal variables (X) to foresee future changes of the growing variable (Y). A causal variable (X) is one that is necessary or sufficient for the occurrence of an event (Y), when it is assumed that X precedes Y in time.

Naïve methods:

$$\boxed{Y_{t-d}, \ldots, Y_{t-2}, Y_{t-1}, Y_t} \rightarrow \boxed{Y_{t+h}}$$

Causal methods:

$$\begin{array}{ccc} \boxed{X_{t-d}, \ldots, X_{t-2}, X_{t-1}, X_t} & \rightarrow & \boxed{X_{t+h}} \\ \downarrow b & & \downarrow b_h \\ \boxed{Y_{t-d}, \ldots, Y_{t-2}, Y_{t-1}, Y_t} & & \boxed{Y_{t+h}} \end{array}$$

Figure 2: Naïve and Causal methods. Adapted from [34].

When the growing mechanism is known, the causal methods can be effective for a long-term forecast. However, naïve methods can be efficient even for hidden growing mechanisms when datasets are available.

SYSTEMS IN COMPETITION, OR WHERE DOES LOGISTIC GROWTH COME FROM?

In order to really understand logistic models and to apply them in the most relevant way, it is necessary to grasp the rationales of logistic growth. Logistic growth is the outcome of a particular form of interaction within a system. For instance in population dynamics, species can compete for a common resource (such as groups fighting for territory), or they can be part of a "biological chain" (as in the predator-prey model). These different interaction schemes generate specific a growth pattern for the species under consideration.

One of the basic assumptions for long-term forecasts that we apply is that all systems evolve under competition according to the law of logistic growth. In techno-economic systems, the growth variable is a frequently applied number of units or marketshare ratio. However, the growth parameter should be defined in accordance with the forecasting task [4]. In order to propose a relevant model of technology forecasting (i.e., a model that can be applied in a way that is reproducible), the nature of the interactions driving technology competition and diffusion must be clarified [13, 35].

In his paper about a scientific approach for managing competition, Modis T. describes[2] six ways that two competitors, can influence each other's growth rate [17]: pure competition, predator-prey, symbiosis, parasitic (win-impervious), symbiotic (loss-indifferent), and no-competition. These concepts have also been developed – with different terms – in economic and management literatures [35].

[2] It is referenced to a study of Kristina Smitalova and Stefan Sujan (1991).

Pure competition – a situation when both species suffer from each other's existence because they exploit the same resources to survive. In economic terms, competition takes place when technologies offer similar functions –technologies that are highly substitutable compete for the same market. However, the literature on imperfect competition shows that pure competition is exceptional: transportation costs, search cost, switching costs or capacity constraints can relax the competition between products [36].

Symbiosis – a situation when both species benefit from their association. For instance, mobile phone sales trigger an increase of operators and new services. Advanced services of mobile phone operators initiate sales of the latest mobile phone models. Situations of complementarity have been vastly discussed in the economics of networks literature [37].

Predator-Prey competition – a relationship in which two 'species' interact as a 'predator' and its 'prey'. These dynamics go on in cycles of growth and decline. In economic terms, the predator-prey situation is characterized by both complementarity and competition as in the "hawk-dove" model. Examples of these situations are found in trade economics [39].

Parasitic (win-impervious) – a relationship between two species in which one obtains some benefit while the other is unaffected. Examples include growth of digital cameras and computers sale that trigger growth of external hard discs market. However, sales of external hard disks do not influent to sales of digital cameras.

This situation is characterized by one-sided complementarity (and indifference from the other side).

Symbiotic (loss-indifferent) – a situation when one party suffers from the existence of the other, which remains insensible to what is happening. In economic terms, this situation refers to well known negative externalities [40] – a concept well suited for analyzing pollution issues for instance.

No-competition - a relationship between two species when there is no overlap in using resources to evolve. For instance, sales of coffee do not affect sales of tea in the same supermarket. Sales depend on seasonal variation rather than on the competition between two products.

In rather simple cases, it would be justified to study the precise pattern of interaction and competition to formulate a specific model of growth useable for specific forecasting. But interaction among competitors are often complex (see the economic literature on technology competition, Arthur 1988) and addressing the issue is likely to become excessively complex, time-consuming and sensitive to arbitrary modeling strategies or even hidden errors and biases. Therefore, we prefer a second option: decomposing the competition system into sub-systems in order to obtain an accurate fit of the model on observed data.

COMPONENT LOGISTIC MODEL

Frequently, due to the difficulties with system definitions, the time-series data cannot be refined and split properly. It leads to inaccuracy with fitting a logistic S-curve to data.

Prior to discussing the component model, a problem-contradiction should be defined: system evolutions should be described by multi-parameter complex functions and

curves, since the systems rarely follow a single S-curve trajectory due to *endogenous* and *exogenous* complexities. However, system evolutions should be described by a simple, three-parameter logistic function, to provide a clear physical interpretation, to be comparable with other systems' evolutions, to decrease errors during forecasting and to be applicable in practice.
In response to the formulated contradiction, the component logistic model proposes a description of the complex growth processes using a combination of simple three-parameter functions by applying bi-logistics [7] or multi-logistics [8]. The mechanism of this combination resembles the principle of the 'nested doll' [1] and once again confirms the fractal feature of natural growth concept [20].
For instance[3], to study the dynamics of US Nuclear tests (source of data [21]) a single simple logistic does not provide the adequate level of residuals (accurate fit), while a bi-logistic growth curve fits data with acceptable residuals (see Figure 3).

Such a result was interpreted the following way: "…the fastest rate of growth (midpoint) of the first pulse occurred in 1963, following the Cuban missile crisis. While the first logistic pulse was largely the race to develop bombs with higher yields, the second pulse, centered in 1983 and nearing saturation now (1994), is probably due to the research on reliability and specific weapons designed for tactical use. The Bi-logistic model predicts that we are at 90% of saturation of the latest pulse. Processes often expire around 90%, though sometimes they overshoot. The residuals show the extraordinary, deviant increase in U.S. tests after the scare of the 1957 sputnik launch…" [7]
When a reasonable interpretation is made, the application of component models provides suggestive and attention-grabbing results. However, our practical experience shows that experts might need several weeks to propose a realistic interpretation for obtained curves.

[3] This example is adopted from [7].

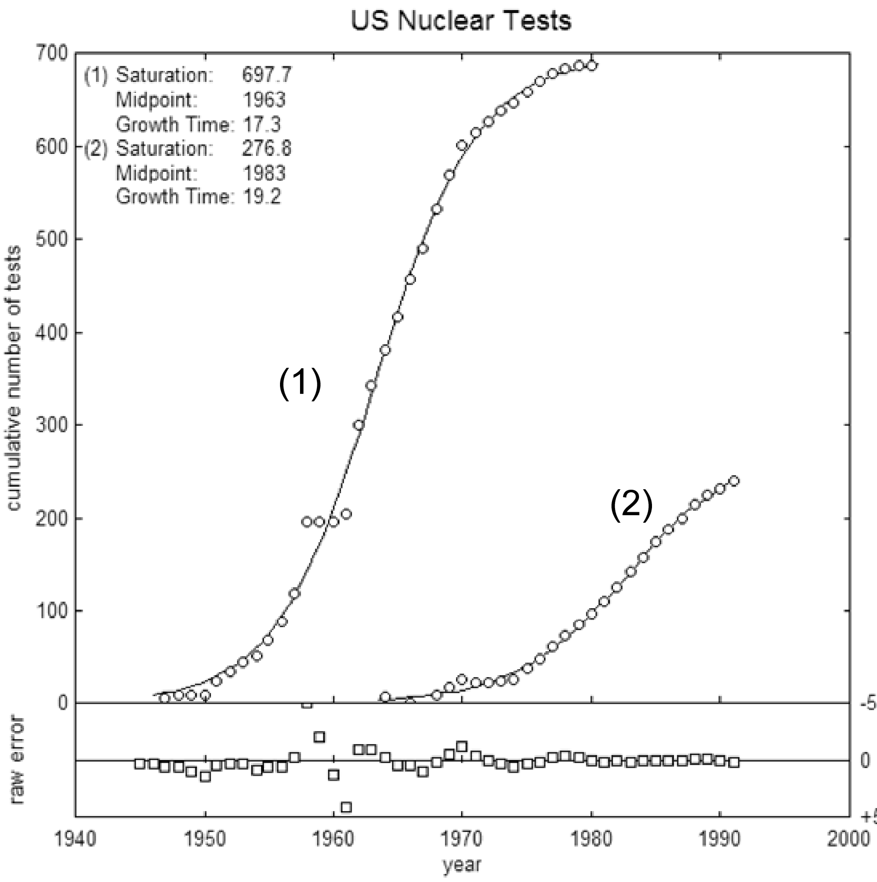

Figure 3: US nuclear weapon tests with decomposed bi-logistic growth curve.

One of the remarkable characteristics of the component logistic model is it helps to understand the observed system through the reduction of residuals and decomposition of the initial dataset by multi-logistic ones the initial definition of the system can be corrected and refined.

APPLYING COMPONENT LOGISTIC GROWTH FOR TECHNOLOGICAL FORECASTING

The component logistic models can be used for testing and validating our view of the innovation process.

INNOVATION PROCESS AS A LEARNING PROCESS

The applied working definition of technology diffusion is the following: technology diffusion is the process of getting a (new) technology adapted through practice. In the context of long-term technological forecasting, technology diffusion can be presented as a process of transition from invention to innovation [14, 22]. For instance, the transitional process from the first feasible prototype to the first regular production and new market creation takes time: for photography - 112 years, for the steam locomotive – 55 years, for rolled wires – 47 years, for the lead battery – 79 years; and for arc welding – 49 years respectively [22].The innovation process can be seen as a sequence of activities which have their own characteristics [27]. In many cases, the

separation between the invention, technical validation and commercial exploitation is justified as each of these phases generates an output to be used by the next phase:
Invention is defined as a result of engineering activities in a technological context; resolving the contradictions between specific needs (how it was perceived) and known laws of nature. The output of the invention process is a feasible solution and working prototype, but not necessarily a patent[4].
Validation aims at producing and testing prototypes under a set of controlled laboratory conditions to obtain a prototype that could be used as a pre-series.
Production and commercialization aim at increasing the added value of the innovation for the producer and the user. This can be done by increasing the productivity itself, by developing the distribution network, or by introducing small modifications to the product to satisfy consumer requests.
Each of these three phases obviously deals with "something" different and we expect that the use of the component logistic models based on this decomposition can yield the required results. But because their purposes are different, one is faced with the difficulty of measuring their "growth" with a common indicator. For instance, the number of sells is a natural growth indicator for the production and commercialization phases, but it has no meaning for the measurement of growth in the other phases. What these phases have in common is that they describe learning processes. Learning relates to the reduction of uncertainties [18]. When enough information and knowledge has been acquired, moving to the new phase of the innovation process is required for further knowledge and information acquisition [27].

WHAT SHOULD BE MEASURED?

Information and knowledge growth is common to the different phases we have described and is a potential growth indicator in the perspective of component logistic forecasting. A preliminary step is to define these concepts in an operational way. The measurability of knowledge and information will be our most important concern. First of all, let us propose the concepts needed to understand what learning actually is about.

Data

Data is a description of facts from a certain viewpoint using known parameters and values (measurement). In other words, it is a description (e.g. measurement) of facts through a comparison with something known (size, color; strength). Data acquisition is limited by examples to compare and selected measurement units (e.g. how does one measure a personal value?) It is important to underline that the same facts can be described by different datasets (e.g. the performance of military aircrafts and of passenger airplanes).

[4] "Patent is a government grant to an inventor assuring him the sole right to make, use, and sell his invention for a limited period." [Collins English Dictionary. 8th Edition, 2006]

Information

Information can be defined as a structured representation using data and interpretations from a certain viewpoint. It is structured, articulated, codified, and stored in certain media. The most common forms of information are manuals, documents, and audio-visual materials. Information is not related to individuals but it has an interpretative content. By watching the daily news from different countries it is easy to witness how different information can be about the same facts and events.

Knowledge

Knowledge is a personal way of using information to manage practical or intellectual tasks. Knowledge always belongs to an individual and includes conscious, subconscious, and unconscious components. Knowledge cannot be placed on the carrying medium since it is dynamic and constantly changing. The applied working definition for "knowledge" is similar to “tacit knowledge”, which was proposed by Michael Polanyi (1951).

In brief, knowledge acquisition can be presented as a result of information that has been assimilated through interpretation, validation and adaptation phases. Knowledge can also take the form of experience based on feedback from practice.

World-view

The totality of our beliefs about reality forms our world-view. In other words, it reflects how we perceive the world. One’s personal view of the world and how one interprets it relies on the dominating world-view in society on the one hand and it influences the transformation of society’s world-view through communication, on the other hand (e.g. ideas of Galileo Galilei). According to our experience, simply having new information does not systematically change one’s world-view. However, regular knowledge acquisition contributes a lot to the evolution of one’s world-view and increased learning capacity.

LAW OF LOGISTIC GROWTH AND EMERGING TECHNOLOGIES

The key question to be answered has been formulated the following way: How can the future of emerging technologies be forecast by using simple logistic S-curves, when there is no statistical data about it?

Before the 'infant mortality threshold' there is no statistical data about growing variables like efficiency, market share or number of ‘species’, since the system does not exist outside of laboratories. How can the logistic S-curve be constructed before having statistical data for the growing variable? The generic question can be reformulated the following way: How can one foresee time, place and specificity of transition from invention to innovation in advance?

The application of causal methods has been suggested to answer the above question. In the first experiment (2004-2005: a forecasting project for small stationary fuel cell) the hypothesis about studying problems (contradictions) as causal variables to foresee the future evolution of technology was tested.

The quantity of contradictions was applied as a unit of measurement to judge technology maturity. The assumption was that at the early stage of study the growth rate of problems is slow, later it increases, and at a certain stage the growth of

contradictions slows down until no new problems are registered. This assumption has been confirmed with the first experiment in 2004-2005 at the European Institute for Energy Research (EIFER, Karlsruhe, Germany) [23]. It was also tested in a project for distributed energy technologies (2005-2006, EIFER) [24]. Several small scale tests performed afterwards showed relevant results as well.
Obtained results which demonstrate conformity with logistic growth, have been recognized as preliminary ones until a explicit measurement mechanism for knowledge acquisition can be proposed.

NETWORKS OF CONTRADICTIONS

For the practical forecasting projects mentioned above, the network of contradictions has been proposed [28] as a knowledge acquisition process guideline. Among many other roles, the network of contradictions helps differentiate signal and noise information-knowledge in the early stages of emerging technologies. The application of networks of contradictions intensifies learning and research processes on the one hand, and facilitates selection of relevant information on the other hand. In addition, a number of contradictions and interlinks between contradictions and critical parameters may be applied as growing variables to depict knowledge growth.
During the practical forecasting projects [3, 23, 24] a slight growth of problems-contradictions were registered at the beginning of the study, fast growing of contradiction number at certain stage of project and decreasing number of problems until stable network at the end.
Networks of contradictions help discover new problems and guide the knowledge acquisition process in accordance with them. The resulting networks of problems on the one hand accumulate information and structure the knowledge of experts; while on the other hand, the construction of maps of contradictions contributes to the reduction of expert bias.
It has also been observed that constructing a network of contradictions helps members of the working team develop their competence more rapidly. This effect takes place as soon as knowledge acquisition is combined with constructing the network. This process produces a system effect when experts are forced to study new limitations for existing and emerging technologies instead of being preoccupied by existing solutions.

GROWTH OF KNOWLEDGE ON THE WAY TO INNOVATION

Currently, the extension of an original concept of 'contradictions as causal variables' for logistic growth is under examination. There are two basic assumptions behind this: 1) any process (especially problem solving) can be considered as a learning process [19, 25]; 2) at the outcome of any learning process, there is a knowledge growth issue. Therefore, it is proposed to measure knowledge growth during the transition from invention to innovation.
In his book [22] Mensch classified innovations based on the date of the first commercial sell and the inventions with the state of the first working prototype. Based on this classification he presented historical data for 113 basic innovations. The distance between invention (feasible prototype) and innovation (first production for market) for different technologies was different. For instance, for electricity

production - 92 years, for dynamite - 23 years, for magnetic tape recording - 39 years, and for fluorescent lightning - 82 years (see working definitions for invention and innovation in section 3.1.)

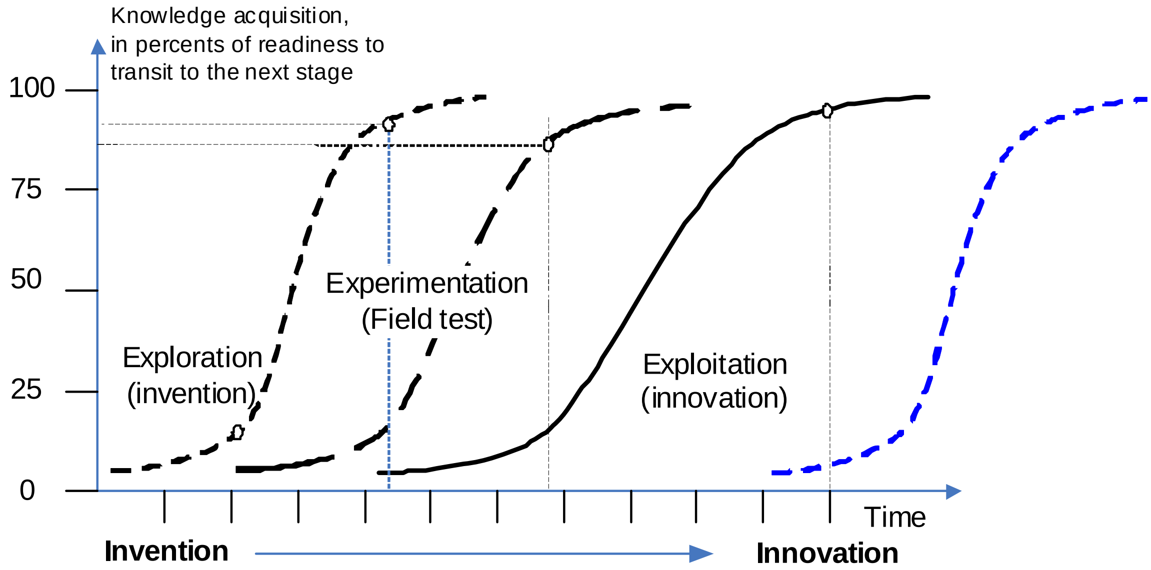

Figure 4: Growth of knowledge within exploration, experimentation and exploitation phases on the way from invention to innovation.

According to the results of research in organization and economic sciences, the transition period from invention to innovation can be described through three consecutive stages [26, 27]: exploration (laboratory research) – E1, experimentation (field tests) – E2, and exploitation (commercialization) – E3.

It can be assumed that at the beginning of the exploration stage (E1), most knowledge is implicit (See Figure 4). At the end of stage E1 knowledge is represented as information mostly in scientific papers and patents. At the experimental stage (E2), the need for sharable information increases, nevertheless, it is necessary to protect intellectual property. Therefore, most of the information at the beginning of E2 can be found in internal reports about field tests, in reviews, and in local patents. At the end of the stage E2, the international patents and publications in industrial journals increase in number; conference papers, and marketing articles are also numerous.

The working assumption is: if we can measure knowledge growth during E1, E2, E3 stages, it gives an opportunity to foresee the beginning of commercialization with the use of logistic S-curves. The amount of knowledge can be applied as a growing variable on the emerging technology.

As an interim solution the relative ratio 'knowledge acquisition in percent of readiness to transition to the next stage' is adopted as a temporary answer for measurement units (see Figure 4). One hundred percent represents the knowledge acquisition ceiling for a certain stage (e.g. exploration). In Figure 4 the broken line curve on the right represents knowledge growth at the exploration stage for the next generation system. It shows that knowledge is accumulated over a period of time and when there is sufficient knowledge (saturation phase) to decide about the next stage, the S-curve of the next stage (e.g. experimentation) passes through its α-point. When accumulated

knowledge approaches 90% of the growth limit, it is time for transition to the next stage.
In practice, the experimentation (field test) stage can be launched before exploration stage of knowledge acquisition reaches the saturation phase. A weak point of the consecutive S-curves model for knowledge is the ambiguity about when the next growth curve will substitute the old one and how to distinguish between these two curves. In order to address this issue the component logistic model which allows decomposing a complex growth process by several simple logistic curves [8] should be employed.
One more fact should be taken into account: all technologies evolve under competition and the number of research projects and amount of funds are limited as well. Hence, it is obvious, why certain inventions have never reached the experimentation stage or some of the inventions which have passed through 70% of experimentation have not arrived at the exploitation phase [18].
A reliable technological forecast should provide an explicit answer to the questions regarding which technology will succeed in competition, when it will happen, and where it will take place. Taking into account described assumptions and models it seems feasible to answer these critical questions.

HOW TO MEASURE KNOWLEDGE?

This crucial question is answered in various specific situations by different way. The detail review of existing knowledge measurement techniques is planned to be done in future publications. In scope of this paper we would like just to point out some fruitful research domains:

- Literature-related discovery [29];
- Patent-based analysis for quantitative estimation of technological impact [30];
- Assessment of knowledge in education [31];
- Measurement of scientific output for different fields [32];
- Text and data mining [33].

Unfortunately, after detail consideration, it becomes evident, that most of the techniques measure not knowledge, but information (see working definition in section *3.2*). Nevertheless, growth of information can be regarded, at certain extend, as indication of knowledge growth.

CONCLUSIONS

The proposed working hypothesis concerning the knowledge acquisition mechanism through problems solving is still theoretical and should be checked through practice. Allowing that knowledge belongs to individuals, measurement for knowledge growth should take into account information growth (e.g. publications) as well as the number of persons involved in the process of knowledge growth. Therefore, it is proposed to measure knowledge as the product of a number of specialists (including authors of information) by number of publications (e.g. patents, conference papers, research reports, journal articles, video-titles and other kind of information).
There are three major working hypotheses to be tested in the near future:

1. To measure knowledge growth by applying a network of contradictions as a guideline to differentiate signal and noise information.
2. To employ the concept of limiting resources from a super-system for validation of the network of contradiction.
3. To adapt the knowledge growth factor as an underlying cause of the technology substitution mechanism.

1. Signal and noise information can be differentiated when one focuses their attention not on the existing technological solutions, but on the problems to be solved regardless of known answers. A network of contradictions is technology to realize the basic principles of system thinking: "First, one should examine their objectives before considering ways of solving a problem. Second, one should begin by describing a system in general terms before proceeding to the specific." [34]
2. The application of simple logistic S-curves to represent growth of knowledge follows the same concept of 'limiting resources' from the nearest super-system as it was implemented to study the evolution of technical systems. For instance, there is a well known situation when, at a certain stage, new laboratory experiments do not provide additional knowledge about a research topic. A typical answer for such a situation is to redesign experiments or to conduct field tests in real conditions but not in a laboratory. An open question for us is the limiting resources in a proposed example. Analysis of limiting resources for constructed networks of contradictions helps to review and validate an obtained map of problems through the study of how formulated problems are recognized in research and development societies. In the same time, study about limiting resources discloses future problems and technological barriers according results of two forecasting project in energy technologies.
3. According to preliminary results of our research, the knowledge growth mechanism is one of the major factors in the chain of technology substitution issues. The competition issue is the exterior side of technology substitution when knowledge acquisition is an internal force for surviving under competition.

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