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Quantitative Technology Forecasting Techniques

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1. Introduction

Projecting technology performance and evolution has been improving over the years. Reliable quantitative forecasting methods have been developed that project the growth, diffusion, and performance of technology in time, including projecting technology substitutions, saturation levels, and performance improvements. These forecasts can be applied at the early stages of technology planning to better predict future technology performance, assure the successful selection of new technology, and to improve technology management overall.

Often what is regarded as a technology forecast is, in essence, simply conjecture, or guessing (albeit intelligent guessing perhaps based on statistical inferences) and usually made by extrapolating recent trends into the future, with perhaps some subjective insight added. Typically, the accuracy of such predictions falls rapidly with distance in time. Quantitative technology forecasting (QTF), on the other hand, includes the study of historic data to identify one of or a combination of several demonstrated technology diffusion or substitution patterns. In the same manner that quantitative models of physical phenomena provide excellent predictions of systems behavior, so do QTF models provide reliable technological performance trajectories.

In practice, a quantitative technology forecast is completed to ascertain with confidence when the projected performance of a technology or system of technologies will occur. Such projections provide reliable time-referenced information when considering cost and performance trade-offs in maintaining, replacing, or migrating a technology, component, or system.

Quantitative technology forecasting includes the study of historic data to identify one of or a combination of several recognized universal technology diffusion or substitution patterns. This chapter introduces various quantitative technology forecasting techniques, discusses how forecasts are conducted, and illustrates their practical use through sample applications.

2. Introduction to quantitative technology forecasting

Quantitative technology forecasting is the process of projecting in time the intersection of human activity and technological capabilities using quantitative methods. For the purposes of forecasting, technology is defined as any human creation that provides a compelling advantage to sustain or improve that creation, such as materials, methods, or systems that displace, support, amplify, or enable human activity in meeting human needs. It will be shown how rates of new technology adoption and rates of change in technology performance take on certain characteristic patterns in time.

A quantitative technology forecast includes the study of historic data to identify one of several common technology diffusion or substitution trends. Patterns to be identified include constant percentage rates of change (such as the so-called "Moore's Law"), logistic growth, logistic substitution, performance envelopes, anthropological invariants, lead/lag (precursor) relationships, and other phenomena. These quantitative projections have proven accurate in modeling and simulating technological and social change in thousands of applications as diverse as consumer electronics and carbon-based primary fuels, on time scales covering only months to spanning centuries.

Invariant, or at least well-bounded, human individual and social behavior, and selected (genetic) human drives underlie technology stasis as well as change. In essence, humans and technology co-evolve in an ecosystem that includes the local environment, our internal physiology, and technology (where the technology can be considered external or complementary physiology). The fundamental reliability of quantitative technology forecasts is being supported by ongoing developments in modeling and simulation derived from systems theory, including complex adaptive systems and other systems of systems research.

Carrying out a quantitative technology forecast includes selecting a technology of interest, gathering historic data related to changes in or adoption of that technology, identifying candidate "compelling advantages" that appear to be drivers of the technology change, and comparing the rate of technology change over time against recognized characteristic patterns of technology change and diffusion. Once a classic pattern is identified, a reliable projection of technology change can be made and appropriate action taken to plan for or meet specific technology function or performance objectives.

QTF as defined here, as it seeks to determine the 'fit' of time-stamped growth or diffusion of technological data to ubiquitous yet mathematically simple models, does not include probabilistic, non-temporal based, or other relational methods that are seeing increased use in data-mining and data visualization efforts in determining technological and social trends. Many commercial products are now available that perform statistical and other algorithmic analyses among data in large databases to determine otherwise indiscernible relationships. Such analyses can be useful, for example, in marketing and sales, business intelligence, and other activities requiring a better understanding of relationships among systems of complex interactions among components or agents, and the system or individual response to change. While these practices do include observing or trending change over time, the analyses usually involve only secondarily linear temporal projections including statistically based measures of uncertainty or risk. Moreover, the focus of these methods is most often understanding or visualizing static or cause-effect relationships, rather than understanding primarily the growth, diffusion, substitution, etc., which are primary foci of the highly temporal-based QTF methods.

2.1 Methodologies

Quantitative technology forecasting has been applied successfully across a broad range of technologies including communications, energy, medicine, transportation, and many other areas.

A quantitative technology forecast will include the study of historic data to identify one of or a combination of several recognized universal technology diffusion or substitution trends. Rates of new technology adoption and rates of change of technology performance characteristics often can be modeled using one of only a relatively small number of common patterns. The discovery of such a pattern indicates that a fundamental diffusion trajectory, envelope curve, or other common pattern has been found and that reliable forecasts then can be made.

The quantitative forecasting techniques are "explanatory principles" (Bateson 1977), that is, sufficient by their reliability for the purposes of modeling technology diffusion patterns and forecasting technology adoption. Many researchers have attempted to develop fundamental theories underlying substantiate the commonly found patterns, such as extending theories of system kinematics and other advanced systems theories, to varying success and acceptance in the field. The ubiquity of the various patterns has been studied also using systems theory and complexity modeling, such as the complex adaptive systems approach.

2.1.1 Logistic growth projection

Forecasters had their first significant successes in predicting technological change when they used exponential models to project new technological and social change (e.g., Malthus, 1798, as cited in). It was deemed only logical that a new technology at first would be selected by one, than perhaps two others, and these people in turn, two others each, and so on, in a pattern of exponential growth. Ultimately however, as in any natural system, a limit or bound on total selections would be reached, leading early researchers to the use of the logistic (or so-called S-curve) to model technological and social change.

In the late 20th Century, researchers in the United States such as Lenz (Lenz, 1985), Martino (Martino, 1972, 1973), and Vanston (Vanston, 1988), and others around the world, such as the very prolific Marchetti (Marchetti 1977, 1994, 1996) refined forecasting methods and showed that the logistic model was an excellent construct for forecasting technological change. The logistic displayed virtually universal application for modelling technology adoption, as well as for modeling effectively many other individual and social behaviors.

The classical logistic curve is given by:

$$P(t) = \kappa/\{1 + \exp[-\alpha(t- \beta)]\} \tag{1}$$

This simple three-point curve is defined by κ, the asymptotic maximum, often called the carrying capacity; α, the rate of change of growth; and β, the inflection point or mid-point of the curve. Figure 1 illustrates the idealized logistic curve of technology adoption or diffusion.

A popular means to visualize the growth match to the ideal logistic curve is by way of a linear transformation of the data. The Fisher-Pry transform (Fisher and Pry 1971) is given by:

$$P'(t) = F(t)/[1 - F(t)], \text{ where } F(t) = P(t)/\kappa \tag{2}$$

where F(t) is the fraction of growth at time t, given by

$$F(t) = P(t)/\kappa \tag{3}$$

The Fisher-Pry transform projects the ratio of per unit complete and per unit remaining of a growth variable.

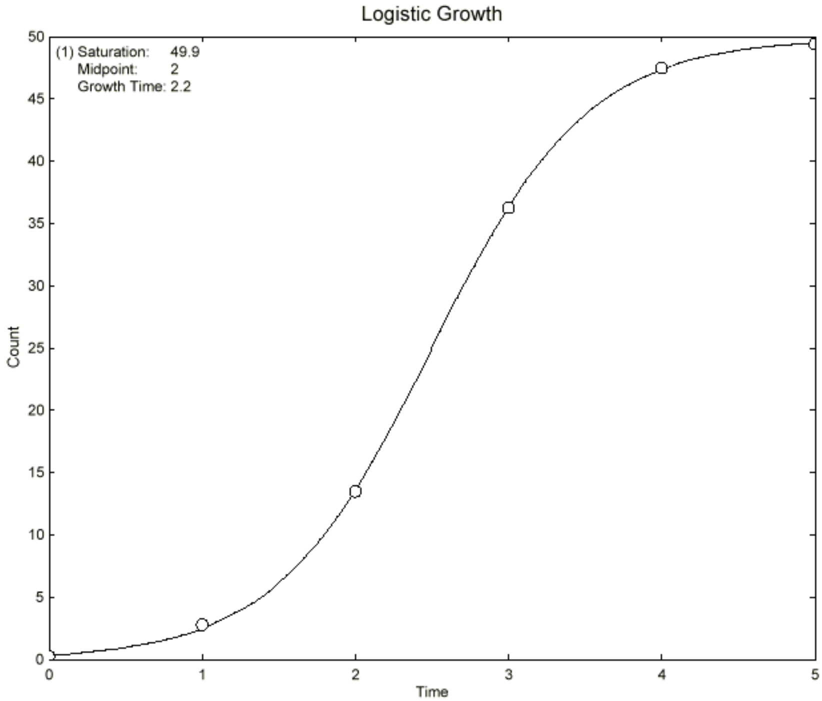

Fig. 1. Ideal logistic growth curve (Adapted from Meyer et al, 1998).

Figure 1 illustrates the idealized logistic curve of technology adoption or diffusion. Figure 2 shows the logistic growth of the supertanker of maritime fleets presented in a popular format developed by Fisher and Pry (Fisher and Pry 1971) that renders the logistic curve linear. Figure 3 shows the growth pattern of a computer virus that infected computers on worldwide networks.

Note that the time and level of saturation (peaking) of the logistic trajectory is a key indicator of change: it can signal the emergence of new or substitute technology.

2.1.2 Constant rate of change (performance envelope)

Technology change occurs within dynamic and complex systems of human behavior. The growth and diffusion of technology influences and is influenced by the activities of humans as individuals and groups at varying scales. The adoption of new technology requires intellectual, material, energy, and other resources to be redirected, increased, and otherwise managed as required in the implementation of the new technology.

When a new technology emerges having the substantive compelling advantage such that it will successfully substitute for an incumbent technology at some higher, but still (physiologically complementary) practical performance level, humans in groups tend to go about the changeover in a methodical way, managing to maintain equilibrium in the vast array of a culture's interaction and interdependent social, material, and economic systems.

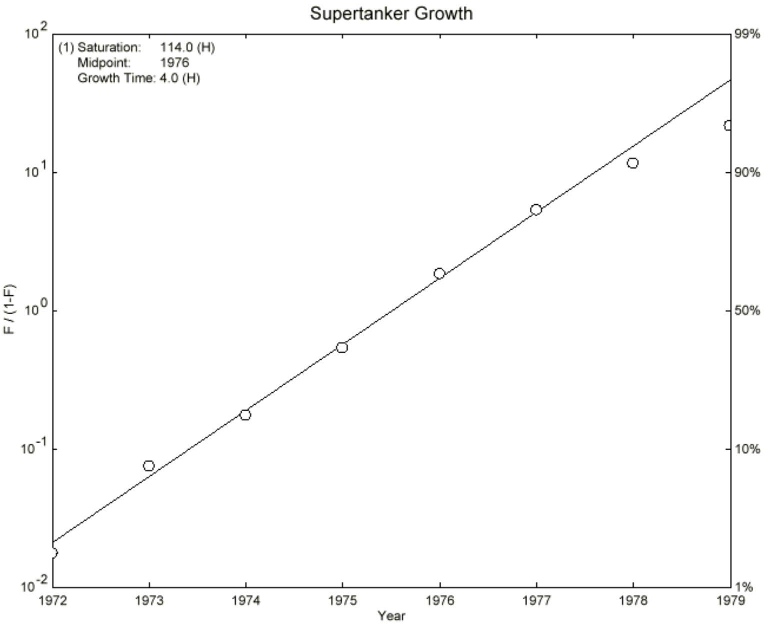

Fig. 2. Logistic growth of the supertanker (Adapted from Modis 1992).

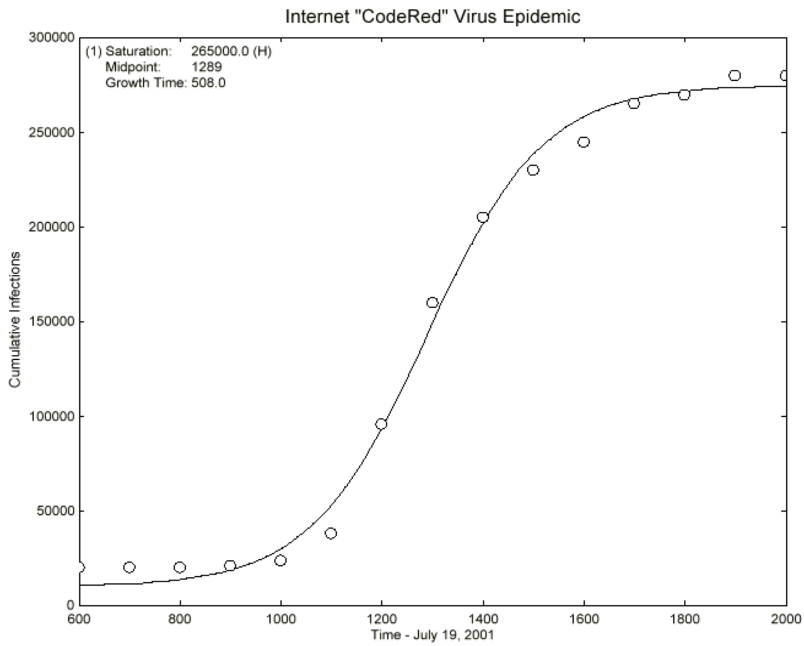

Fig. 3. Logistic growth of a network computer virus (Data from Danyliw and Householder, 2001).

The result suggests strongly that the adoption and change of substitute technologies is far from random and rarely sudden, and usually follows a smooth transition, at a rate of change dependent on the either consciously or unconsciously maintained by individual and collective forces for equilibrium.

This result contradicts theories of “disruptive technology”. It is true that individuals or subgroups can face significant disruption when a new technology arrives and displaces, especially if rapidly, the incumbent technology. However, QTF research suggests that careful study can unveil the technological or physiological parameter that governs or paces the technological changeover, reflected in a smooth trajectory of the change characteristic on a larger scale. Marchetti commented, “Show me the disrupting technology, and I will find you the logistic curve”, (personal communication, February 2007).

Forecasters call the curve of sequential performance levels of adopted technologies a *performance characteristic curve*, and search for its telltale shape in the history of a technological area of interest. The nature of the curve is exponential growth, where, if a quantity x depends exponentially on time t the growth expression is

$$x(t) = \alpha^{b/\tau} \tag{4}$$

where the constant a is the initial value of x,

$$x(0) = \alpha \tag{5}$$

and the constant b is a positive growth factor, and τ is the time required for x to increase by a factor of b.

Figure 4 shows an example of the performance characteristic curve for transistor density on a microprocessor chip, the popular “Moore’s Law”. Intel CEO Gordon Moore could target the timing of the introduction of new technology performance and thereby target R&D efforts to a horizon performance. The performance envelope shows that the successful emergence and integration of a new technology can be predicted inversely, i.e., *the performance envelope provides a future order of merit that an incubating technology must achieve*. In other words, the horizon drives the technology, not the other way around.

Figure 5 shows the performance envelope history of primary industrial energy conversion. Note that the performance trajectory technique identifies the horizon of expected technological performance, in this case, an energy conversion efficiency of about 75% in 2050. Along this trajectory, we see that only fuel cell technologies, of all emerging energy conversion technologies, are capable of meeting the 2050 efficiency horizon.

Core performance envelopes have been identified in many industries, and likely exist for all industries and technology areas. The performance envelope is a valuable index and decision tool for technology planning, including technology watch and horizon scanning activities.

2.1.3 Logistic substitution

Transitions from one technology or performance level to the next tend to follow neat, manageable patterns. In the 1960’s, Fisher and Pry (Fisher and Pry 1971) analyzed hundreds of technological substitutions in history and devised a method to graph the substitution

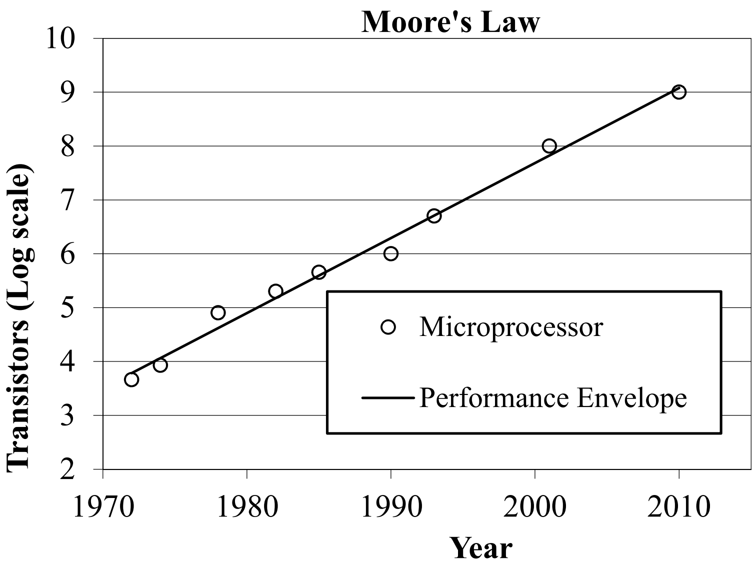

Fig. 4. Moore's Law - Performance envelope of microchip transistor density (Data from Intel Corp. 2001)

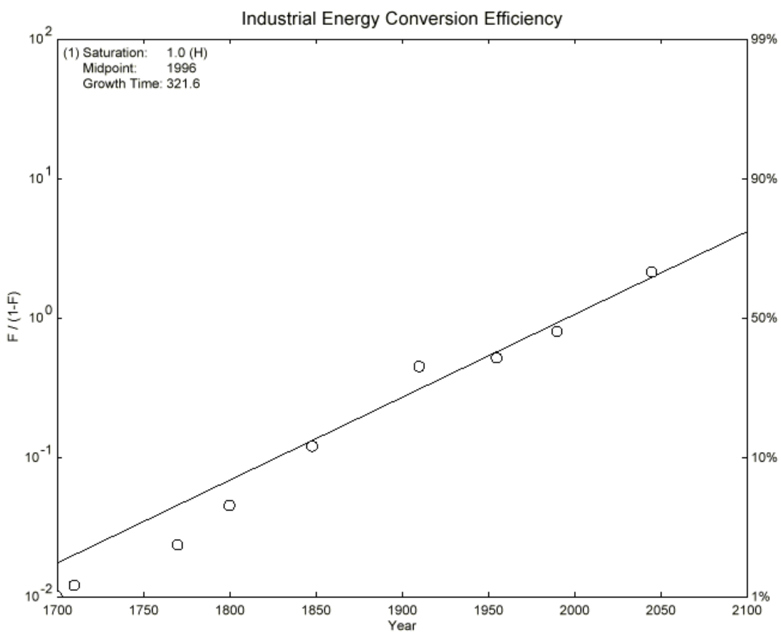

Fig. 5. Performance envelope of industrial energy conversion technology, projection to 2050 (Adapted from Ausubel and Marchetti, 1997).

patterns in linear form. The curve-fit is more easily estimated by observation of the straight line of the Fisher-Pry transform as compared to estimating fit along the sweeping logistic curve.

Figure 6 illustrates a typical logistic substitution pattern, here the substitution of automobiles for horses as the preferred 'personal vehicle' for transportation. Studies have identified the logistic substitution pattern in technologies as diverse as substitutions in fiber optic transmission networks (Vanston 2008) and the substitution of latex for oil-based paints (Modis 1992). In the maritime industry there evolved a multiple-pulse logistic substitution of motor-over-steam-over-sail in ship propulsion technology (Figure 7).

Being able to predict the emergence and diffusion of substitute (often disruptive, on local scales) technology is a powerful tool in any comprehensive, strategic technology watch program. Knowing the trajectory of an overcoming technology enables reliable projections of critical time horizons of technology change. QTF Logistic Substitution provides a straightforward method to illuminate these evolving patterns of current and future events.

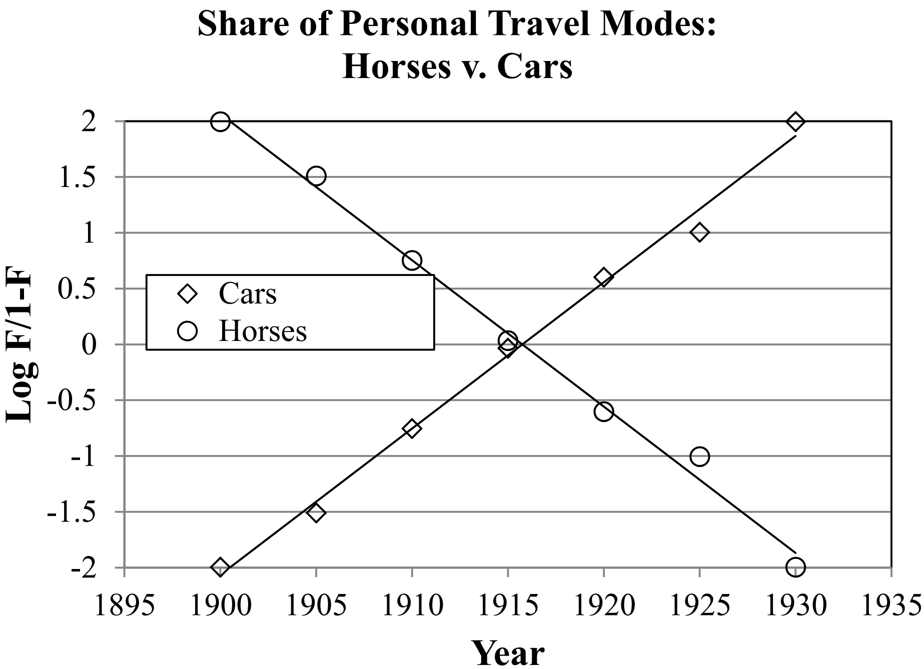

Fig. 6. Logistic substitution of primary personal travel mode (Fisher-Pry display format).

2.1.4 Precursor (lead-lag) growth relationship

The implementation or adoption of a technology has been shown to vary logistically. When one technology is dependent on or otherwise closely related to a previous development, the two trajectories are found to synchronize in a steady lead-lag relationship (see Figure 8).

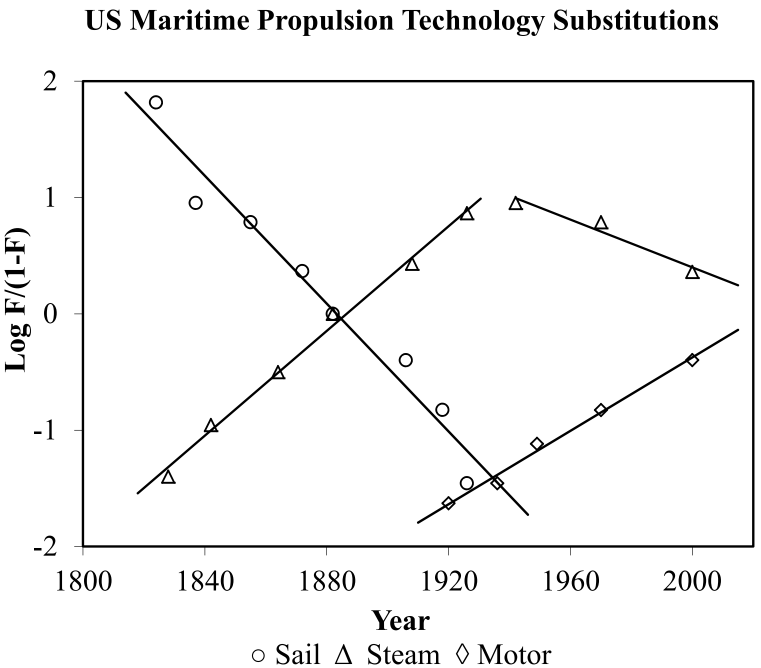

Fig. 7. Substitution of US maritime propulsion technology (Adapted from Modis 1992).

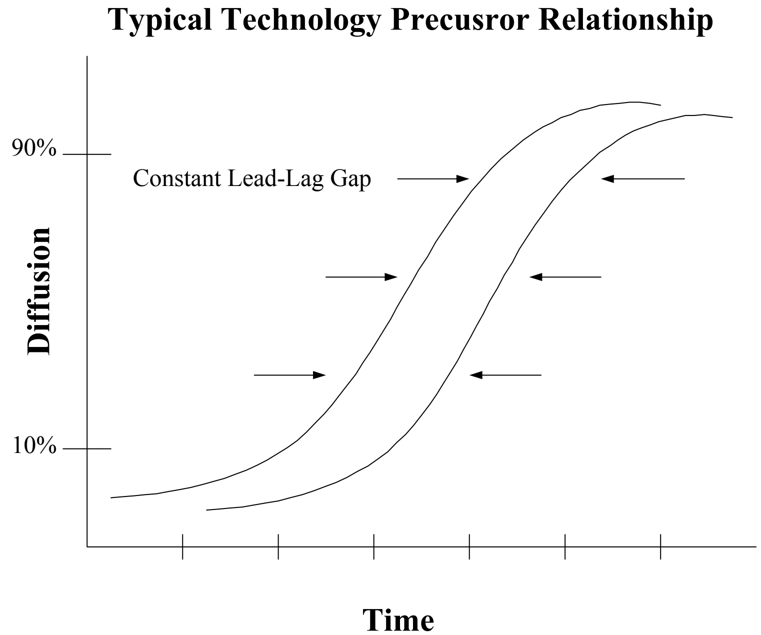

Fig. 8. Constant lead-lag logistic relationship.

Studies have shown that the worldwide discovery of petroleum resources has led the production of oil by a fixed period over many decades (Modis 2000). Studies have shown also that the diffusion in the USA industry of networked desktop personal computers followed the same shape logistic trajectory as the precursor technology, stand-alone PCs (Poitras and Hodges 1996).

Figure 9 shows the lead-lag relationship between patents and research publications in quantum dot technology. Academic publications and US patent office databases were mined to capture the two parallel logistic growth pulses. Notice again the nearly constant 4-year time lag from beginning to end of the pulses. It would have been readily forecast around the year 2000 that within six more years the early patent pulse would end and quantum dot technology would next evolve into broad applications and commercial viability.

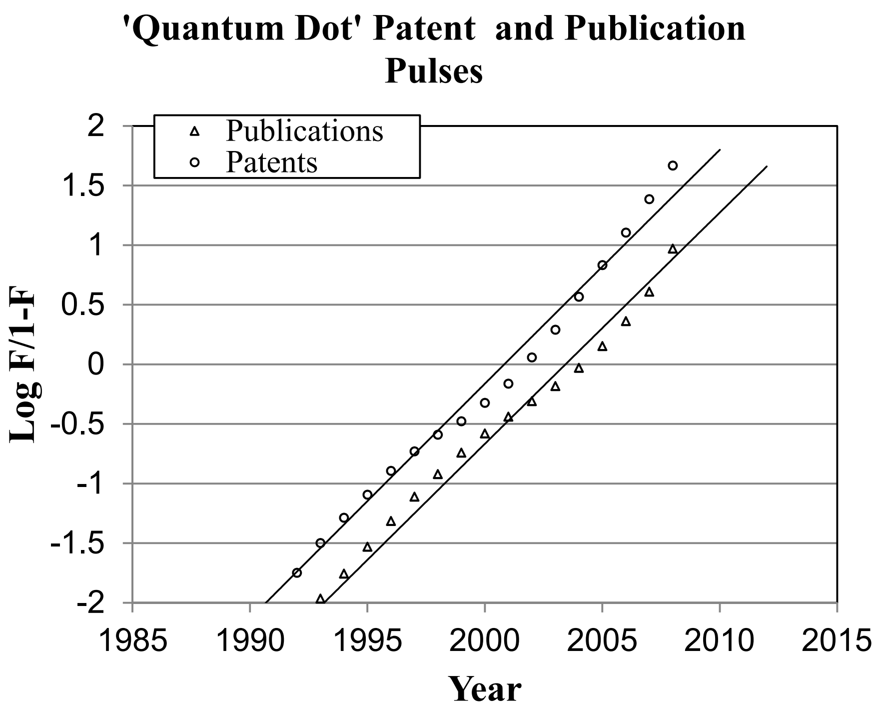

Fig. 9. Approximate constant 2-year precursor relationship between quantum dot technology patents and publications (Data from Walk 2011b).

2.1.5 Anthropological invariants

In the grand history of the progression of technological change, one of the striking results is evidence, otherwise not identified or identifiable, of the invariance of certain human behaviors. While technologies offer many and perhaps infinite varieties of how to get things done, the things humans do want to get done, generally, have remained the same for hundreds and thousands, and perhaps millions of years. For example, travel and communication patterns, depicted in broad averages of commuting or foraging times, or in numbers of human exchanges, have been shown to be constant across time and cultures.

In the case of the commuter, the average commute in the United States has remained at about one half hour since the automobile became the main choice of personal mobility a century ago. The advice to automobile manufacturers is that seat design need only accommodate the average drive, about 30 minutes. No matter how much the manufacturer's investment, no matter how much more advertised, the average user is going to drive the automobile a half hour per day, out and back.

The compelling advantages in the design and performance of technologies can be viewed as artifacts of unchanging human behavioral preferences. As an example, Figure 10 shows the more or less constant acceptable (and, by complex social feedback mechanisms, so engineered and designed) risk of death by automobile in the United States, over nearly an entire century.

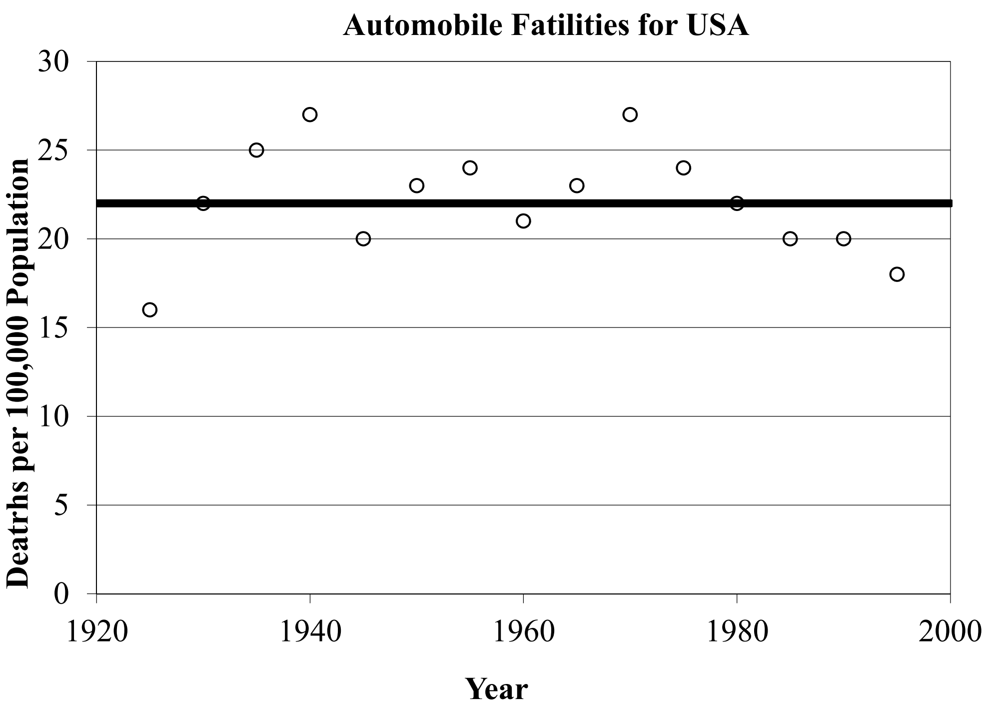

Fig. 10. Risk of having a fatal automobile accident in the US (Adapted from Marchetti 1994).

2.2 Sample published QTF applications

Thousands of studies using QTF techniques to project or monitor technological change have resulted in identifying the underlying logistic, performance envelope, substitution, or other ubiquitous fundamental trajectory. Table 1 provides a very short list of sample published studies.

Sections 2.2.1 and 2.2.2 provide further examples of QTF studies with more in depth discussion of the process of understanding and extracting strategic meaning from study results.

QTF Technique	Application	Publication Source
Logistic Growth	Aluminum in Automobiles	Bright 1973
	Commercial Space Launches	Walk 2011a
Logistic Substitution	Popular Recording Media	Meyer, et al 1999
	World Primary Energy Substitution	Marchetti 2000
Performance Envelope	Hard Drive Density	Christenson 1997
	Internet Bandwidth	Nielsen 2011
Precursors	Oil Discovery and Use	Modis 2000
	FORTRAN	Walk 2011b
Anthropological Invariant	Age of world shipping fleet casualties	Walk 2004
	Share price of DJIA stock	Modis 1992

Table 1. Sample QTF published studies

2.2.1 Human travel: Wanderlust, exploration, and settlements

Marchetti published a remarkable series of quantified technological studies of the locomotive habits of humans (Marchetti 1994). Modis (Modis 1992) provides a very interesting graph of the ‘discovery’ of the Americas, of which Figure 11 is an adaptation. While many interesting insights flow from this remarkably simple set of sailings across the Atlantic, the reader’s attention is called to the fundamentally logistic growth in probing the New World.

The proceeding graphs (Figures 12 to 14) show human exploration patterns of our sailings across space: to the Moon, Venus, and Mars. The Mars probes were plotted using a 5-year running average to smooth the clusters of probes launched when Mars and Earth were in optimal launch positions. Note the two distinct pulses of Mars probe activity, the second approaching 90% of saturation at the time of writing this chapter. These various space probe logistic patterns would be nearly interchangeable if we were to normalize scales.

At the end of the logistic saturation in Columbus’ era, in the early 1700’s, ‘permanent’ settlements in the ‘new’ world had been established and commercial trade was in early flourish. The ‘new’ world was much like the ‘old’ world in almost every aspect of habitability, our legacy of inherited survival needs could be met readily, and so we relocated.

The logistic pattern of discovery, of which the probes to the ‘new world’ are an excellent example, is repeated in space explorations. However, the probes have not been followed by the settlements and commercial trade phase.

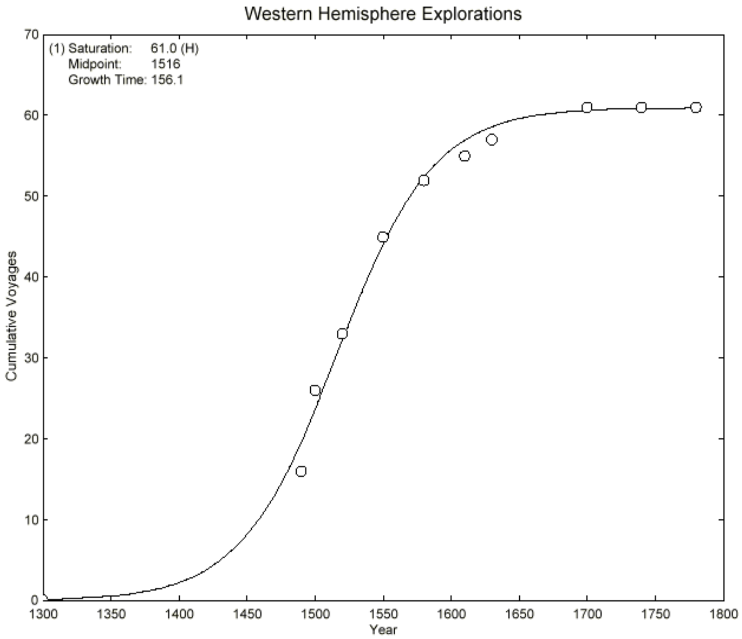

Fig. 11. Logistic pattern of discovery voyages of the Western Hemisphere (Adapted from Modis 1992).

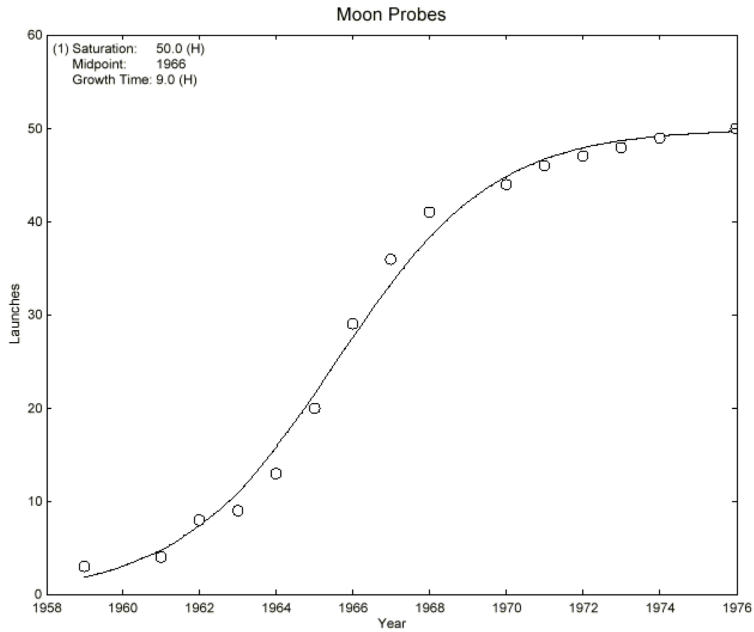

Fig. 12. Logistic growth of Moon Probes (Data from NASA 1958-1976)

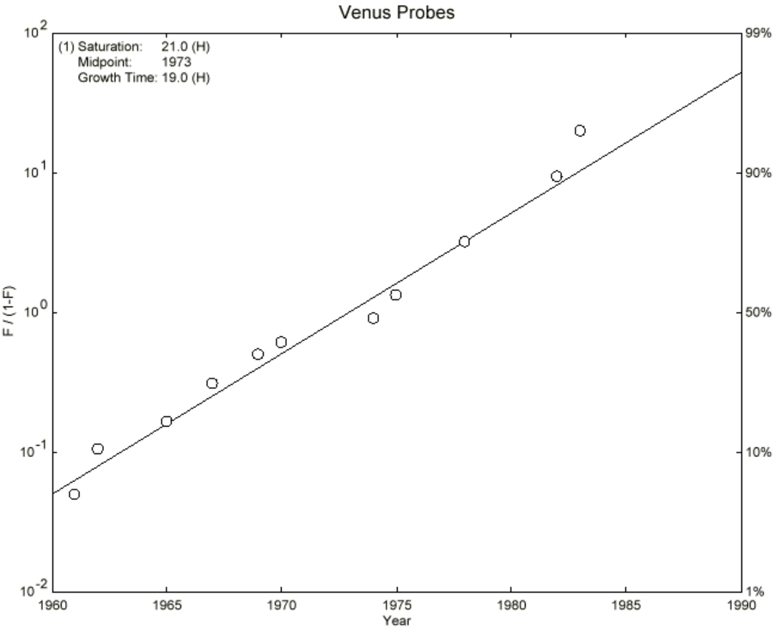

Fig. 13. Logistic growth of Venus Probes (Data from NASA 1960-1990)

Let us consider, in this example, what the consistent patterns in world and solar system probes might tell us. Among many things, the studies tell us what is obvious, but that can be lost in heady visions of technology promise: we simply do not inhabit places we do not like after having visited them. QTF studies have shown there exist identified and unidentified, i.e., conscious or unconscious, invariants in human behavior apparently lain down by millions of years of gene-coded and cultural evolution that we cannot override by our wishing, will, or law. For example, after exploring the far polar regions, by air, on land, and under the sea, people have not settled there. The landscapes simply are too inhospitable, the criteria of hospitableness being a short list of bounded behaviors and needs, some identified in the history of technological adoption and change. We have not built cities under the sea, as was projected by futurists and popular media in the late 20thcentury, and QTF perspectives indicate it is extremely unlikely we ever will.

We might, then, consider seriously that we have reached the end of our Moon, Venus, and Mars explorations, and that the idea of anyone ever settling either Moon, Mars, or Venus, is a wish fading from our collective mind.

The results of this sample QTF study suggest a larger perspective on space travel. Humans have learned to travel the ocean, and even penetrate a short distance beneath its surface to travel and meet other physiological (e.g., nutritional) needs, but we have not chosen to live below the ocean surface. We can look at this frontier geometrically, as that of a well-traveled outer spherical surface of a downwardly vast and uninhabitable ocean of water.

We can look at the space frontier by an analogous geometrical stretch of the imagination. Consider our very active and frequently travelled low earth orbit (LEO, up to 2000 km)

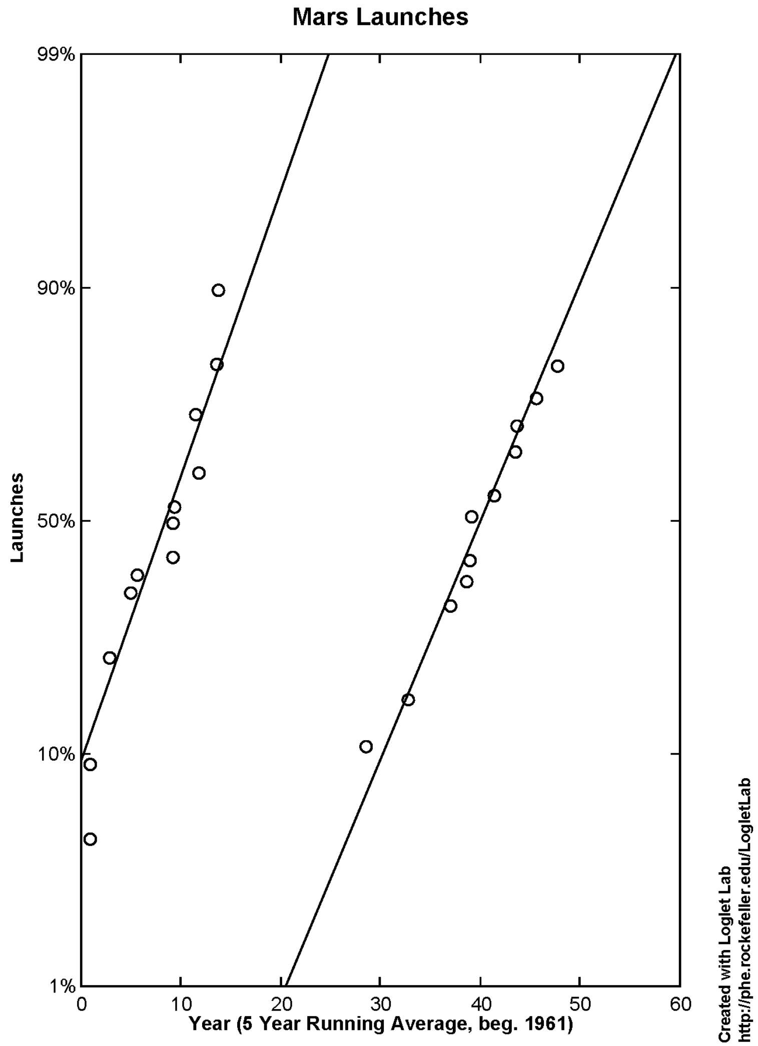

Fig. 14. Two-pulse logistic growth of Mars Probes (Data from NASA 1961-2011)

sphere as an interior spherical surface of an outwardly vast ocean of space. We have learned to travel this space ocean 'surface', and even penetrated to a short distance (in a radially outward direction, such as across our solar system). However, we appear to be balking on habitations to any 'depth' of space beyond LEO.

2.2.2 Sample of linked research and production trajectories

Figure 15 reveals an interesting and telling symmetry in the superposition of the logistic diffusions of supertankers and engineering publications related to supertankers. The initial publication citations began about 20 years before the commencement of commercial

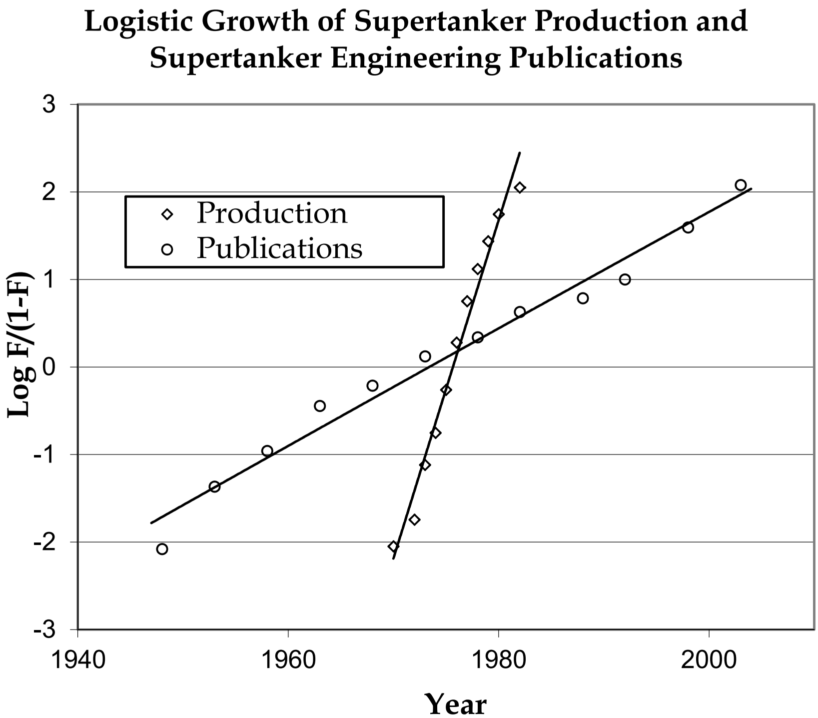

Fig. 15. Growth of research and production of supertankers (Production data from Modis 1992. Publication data by search of Compendex database.)

production, and ended about the same period following the cessation of production. The year of peak rates of growth of publications and production, the mid-points of the logistic curves, was the same. We wrote about them, built them, and wrote about them some more, in a tightly choreographed *pas de deux* of logistic movement.

Note the advantage of such information in technology watch and horizon scanning programs: knowing the relationship between publications and production can yield important timing intelligence for both trending technology and performance trajectories or diffusion in a technology watch program, and for timing of peak saturation and likely emergence of new technology in a horizon scanning program.

3. Typical QTF study procedures and practical considerations

The following tasks outline the typical procedure followed in a QTF study effort.

1. Identify candidate forecast technologies for which the following criteria are met:
   - The technology or technology performance requirement lies on a critical path in a strategic development plan or in a specific program requirement.
   - Reliably accurate, time-referenced data of prior technology adoption rates or performance change rates are available quickly and at reasonable cost.
   - The forecast can be prepared in no longer than three months

- The forecast will provide the opportunity to undertake follow-on forecasts, either by further increasing the forecast scope or scale in the selected technology, or by branching into related technologies or applications.

2. Select the best candidate technology or technology performance requirement for the project based on the selection criteria.
3. Gather experts in the history, application, or research and development of the selected technology or performance requirement.
4. Hold discussions that stress conceptual thinking to develop hypotheses of 1) the (single) performance criteria that led to the adoption, substitution, and overall evolution of the technology, and 2) the (fundamental) human utility driving the technology changes.
5. Obtain time-referenced data to test the hypotheses developed in the expert discussions.
6. Analyze the results of the forecasts.
   - Revisit, clarify, and reaffirm the rationale of the hypotheses underlying the forecast.
   - Corroborate the results, if possible, through the analysis of analogous or parallel technology change.
   - Consider future extreme external events that could significantly influence the forecast.
7. Repeat steps 1-6 for other candidate critical technologies, and learning from the outcomes of the forecasts, identify further opportunities for routine technology forecasting in future technology planning and development.

3.1 Determining growth metrics

Quantitative technology forecasts focus on changes in time of fundamental characteristics of technologies or systems of technologies. While the models and mathematics are relatively simple, time-based, quantitative constructs, expertise in the technology, social regime, or other discipline of the studied data is required to identify the index (metric or measure) that is the locus of change, and which becomes the variable on the vertical scale of the plots, and to assure the reliability of subsequent forecasts. A look back at the many sample plots in this chapter show a wide variety of indices. Often, the index or metric is not an intuitive measure. The reader is encouraged to review the indices identified in achieving the published results shown in Table 1 to observe the wide variation in metrics, and to note those metrics that at first blush might not be considered in initial trajectory analyses.

It is important to remember in all cases that *successful* technological innovation, technology change, and technology performance are linked fundamentally to relatively narrowly invariant behaviors or strong preferences in human needs and behavior. Candidate 'improved' or 'next-generation' technologies must match individual human or socially advantageous human needs and capabilities to survive. Too fast, too small, too big, and so forth, and the new technology will fail, i.e., not be adopted, even though it might provide significant 'improvement' in some performance measure. Technology can be said to be simply extended physiology, and those technologies that have too high a behavior penalty or too low a behavior advantage will not be chosen.

As an example of this phenomena, the commercial airline industry growth was found to follow a performance trajectory based on a metric including passenger seat and speed (Bright and Schoeman, 1973). The number of seats and cruising speeds were logical and intuitive candidates for metrics of airline performance change over time. However, taken individually, each variable yielded no common pattern over time. However, the product of the two yielded an impressive "Moore's Law" for commercial airlines, consistent over more than six decades of development. Considering the product further, it did appear that it did indeed represent a logical growth index. Little advantage is gained if only one of these variables is increased in airliner design, with a result of a lot of people travelling only slowly, or only a few people travelling but very fast. The combination makes intuitive sense, however, with more people going faster simultaneously and increasingly and at a steady rate of change, resulting in an age of low cost frequent travel for the majority of people living in the industrialized world.

Another substantiating and plausible characterization lies in the physics of the change in airliner performance: assuming increasing passenger seats means increasing size and thus mass (though not necessarily in a linear relationship), the trajectory in time can be seen as a continuous improvement in momentum: mass times velocity.

3.2 Curve-fitting and forecast assessment

The goal in a QTF study is to develop the best-fit logistic (or other) curve from the available data. Least-squares fit and other common curve-fitting and valuation methods apply. Researchers at Rockefeller University (Meyer et al, 1999) developed and have made available curve-fitting software that provides real-time interfaces to modify, for instance, logistic equation constants (midpoint, saturation level, and slope) to visualize the best fit curve. Almost any commercial modeling and simulation software program that allows custom equation entry and automatic curve-fitting will provide satisfactory means to develop and best-fit curves to data. Debecker and Modis (Debecker and Modis, 1994) have published a broad investigation of logistic curve development and have suggested quality indices to evaluate the reliability of projecting forward from a plot of limited available data. Meyer (Meyer 1996) also describes several means to derive confidence indices to assess the quality, and thus forecast reliability, of a curve-fit to data in the case of logistic modeling.

3.3 Advantages of QTF

Technology forecasting is receiving increasing interest in private industry and government agencies as leaders and decision makers consider the potential damage of so-called disruptive technologies and loss of competitive advantage in areas such as national defense and security. Many methods have been and are being developed to forecast technology change exclusive of QTF techniques. Some of the forecasting methods rely on drawing qualitative consensus from gathered expert opinion (Delphi method) or performing extensive probabilities-based numerical analyses on vast databases of accumulated information (complex domain forecasting) for example from social networks.

As a conceptual framework, QTF *avoids all* of the following problems associated with the expert and complex domain forecasting methods:

- Methods that are subjective, labor-intensive, reliant on qualitative analysis, un-scalable, un-integrated, and generally untested
- Approaches to technology forecasting are often narrow in scope, focus, and applicability

- Systems that ingest and store up to petabytes of information and require internal cleaning and manipulation before analysis
- Products that leverage social network analysis that do not perform entity disambiguation
- Technologies that analyze social data for trends usually focused on one type or source of data or focus on one subject area
- Technologies that predict events or trends built on proprietary approaches that cannot be independently scrutinized

In addition, QTF techniques *can meet* the following long-term needs as a practical conceptual framework:

- Can be automated, gathering archived and streaming data and self-generating and self-evaluation diffusion and performance patterns
- Can be applied as a unifying conceptual framework to address all types of questions regarding technology forecasting, including both technology watch and horizon scanning.

QTF requires only that the data or information have a time signature. Data can be mined from stored databases such as publications, government agency, and non-government (commercial, private, institutional, etc.) databases. Real-time or near-real time data is harnessable from Internet, social network, and other communications data streams to complement or supplement stored historic data or to analyze and track change on a finer, near-term, time scale.

3.4 Risks and challenges of QTF

Careful review is necessary of forecasts and trajectories or the identification of a potential anthropological invariants, and standard procedure calls for expert review of the data and metrics used in a study, as noted in Sections 3, 3.1, and 3.2. One risk and one challenge stand out as important and frequent hindrances to an organization's application, adoption, and acceptance of QTF techniques to replace or supplement expert opinion methods or deep data analysis approaches.

1. Resistance to new and less complex forecasting techniques despite persistent unreliability and maintainability of expert and probabilistic methods. Massive data mining and deep analysis programs are finding very wide diffusion at the time of this writing following certain success in their ability to identify data trends that can be leveraged for business or strategic advantage. The models are not necessarily designed for technology forecasting applications, but have some direct and indirect value. In comparison, QTF can appear to be a retrograde analytical approach, what with only 3-paremeter equations and the simplest mathematical growth curves. However potent or reliable, the QTF methods can be misjudged and overlooked.
2. Unavailability of time-stamped data in a critical area of interest. Data is not always stored in time-based data sets, or in performance indices or quantities of interest. Commercial data services are available but can be costly. Government-reported data usually is very useful, but is limited often to general information on public utilities such as transportation, communications, etc., data.

3.5 Commercially available and dedicated software

All the curves used in QTF studies can be created in any number of software packages, such as Microsoft's EXCEL, Parametric Technology's MATHCAD, or Mathwork's MATLAB. Several analytical packages have been developed specifically for technology forecasting and are available without charge, including Loglet1 and Loglet2 by the Program for the human Environment at Rockefeller University (http://phe.rockefeller.edu/LogletLab) and IIASA Logistic Substitution Model II by the International Institute for Applied Systems Analysis (http://www.iiasa.ac.at/Research/TNT/WEB/Software/LSM2/lsm2-index.html).

4. Ongoing research

Research continues to better understand the applicability of the logistic (or performance envelope) curves in diverse technological and social change phenomena. Synergies have evolved between QTF techniques and advances in modeling and simulation, especially in the areas of complex adaptive systems and evolutionary systems. The attempts are to derive more complex parametric models of technology and social change to validate the consistency of the heuristic and aggregate QTF models (see, for example, Linstone 2011, Eriksson 2008, and Könnölä, et al, 2007).

5. Conclusion

Quantitative technology forecasting includes the study of historic data to identify one of or a combination of several recognized universal technology diffusion or substitution patterns. This chapter has introduced various quantitative technology forecasting techniques, discussed how forecasts are conducted, and illustrated their practical use through sample applications.

QTF is founded on relatively simple mathematical models portraying diffusion or growth. Systems and systems of systems can exhibit very complex behavior yet result in the emergence of common trajectories of output or outcomes. QTF captures these emergent phenomena to characterize technological change in reliable, repeatable techniques embodied in logistic and performance envelope curves in time.

QTF techniques depend only on compilations of time-stamped data or information to develop reliable trajectories along the simple two- or three-parameter models. Broadly successful forecasts of diffusion and performance patterns have utilized such data as bibliometric, citation, authorship, and patent analyses, and activity such as in social networks, search engine patterns, government agency statistics databases, and many other sources of time-configured data and information. Additionally, while it might seem logical to utilize all available data to generate a QTF (e.g., all patents ever issued, or all papers ever published, on a particular technology topic), the power of the QTF methods is that they typically require only a sampling (or subset) of data and information to generate a valid curve as well as maintain, or update, that curve over time. This translates to significant savings on data and resources to implement strategic technology watch or horizon scanning activity.

A QTF-based technology forecasting framework can integrate readily the *quantitative* outcomes of *qualitative* forecasts produced, for example, by such methods as expert surveys, Bayesian, agent-based, and other disparate types of analyses, thereby increasing the validity and reliability of the expert- or probabilistic-based projections. For example, while a single survey of subject matter experts might not add significant quantitative information to a certain technology projection, a *progression of surveys* over time can unveil the emergence, diffusion, and saturation level of technological ideas, attitudes, and valuations, etc. When incorporated in the QTF-based technology forecasting framework, such information helps create the full, reliable picture of the dynamics of the adoption – or rejection – of technological change.

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Technological change is today central to the theory of economic growth. It is recognised as an important driver of productivity growth and the emergence of new products from which consumers derive welfare. It depends not only on the work of scientists and engineers, but also on a wider range of economic and societal factors, including institutions such as intellectual property rights and corporate governance, the operation of markets, a range of governmental policies (science and technology policy, innovation policy, macroeconomic policy,competition policy, etc.), historical specificities, etc. Given that technology is explicitly taken up in the strategies and policies of governments and firms, and new actors both in the national and international arenas become involved, understanding the nature and dynamics of technology is on demand. I anticipate that this book will decisively contribute in this regard.