

AC 2010-1945: INCREASING TECHNOLOGICAL LITERACY THROUGH IMPROVED UNDERSTANDING OF TECHNOLOGY EMERGENCE AND DIFFUSION

Steven Walk, Old Dominion University

Steven R. Walk, PE, is Assistant Professor of Electrical Engineering Technology at Old Dominion University, Norfolk, Virginia. He recently was head of the Center for Technology Forecasting, and Director of the Maritime-Aerospace Liaison and Technology Development Center, at Maine Maritime Academy, Castine, Maine. His research interests include high voltage electromagnetic phenomena, energy conversion systems, technology management, and technological change and social forecasting. Mr. Walk is owner and founder of Technology Intelligence, a management consulting company in Chesapeake, Virginia, and conducts management workshops introducing innovative strategies for business and technology management.

He earned a BSEET degree, Summa cum Laude, at the University of Pittsburgh at Johnstown and a MSEE degree at the University of Pittsburgh, where he was a University Scholar. Mr. Walk can be contacted at the Frank Batten College of Engineering and Technology, 211C Kaufman Hall, Old Dominion University, Norfolk, Virginia 23529. Telephone 757-683-5713, cell 757-651-1301, or email at swalk@odu.edu.

Increasing Technological Literacy through Improved Understanding of Technology Emergence and Diffusion

Abstract

Understanding technology change and how to influence the process has been identified as a critical societal problem, and efforts to define and increase technological literacy have been underway as an approach to solving the problem. Technological literacy cannot be complete, therefore, without an understanding of major processes of technological and social change.

Contrary to popular wisdom and belief, the emergence and diffusion of new technology is a relatively orderly and predictable process. Successful results in the forecasting of technological change have given fresh perspectives on acceptance criteria and adoption rates of new technology. Quantitative technology forecasting studies have proven reliable in projecting in time technological and social change using relatively simple models such as logistic growth and substitution patterns, precursor relationships, constant performance improvement rates of change, and the identification of anthropologically invariant behaviors. In addition, extensive studies of the evolution of patents have uncovered not a series of breakthrough discoveries or creations, but predictable trends of incremental technological innovation, governed by a short list of parametric variations.

This paper presents an overview of the major processes describing technological change indentified through quantitative technology forecasting techniques, and the author provides several examples of his experiences researching and applying the methodologies. The author shares his experience introducing the concepts and sample studies in discussions of career and personal technology choices with undergraduate students in introduction to engineering and engineering technology courses.

Introduction

Literacy in technology, including knowledge of technological and social change, has been cited in various organization and research publications^{1,2,3} as cornerstone to maintaining social, cultural, and economic progress in the United States and around the world. The means to model and project technological and social change 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 any stage of a technology lifecycle to better predict future technology performance, assess the impact of technological change, and improve technology planning and investment. Knowledge of such means to understand and project paths of technology and innovation would constitute important content in a technology literacy program.

Often what is published as a technology forecast is simply scenario planning, usually made by extrapolating current 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 recognized universal technology diffusion or substitution patterns. In the same manner that quantitative models of physical phenomena provide excellent predictions of system 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

Quantitative technology forecasting is the process of projecting in time the intersection of social needs 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. It has been shown that rates of new technology adoption and rates of change in technology performance take on characteristic patterns in time.

A quantitative technology forecast includes the study of historic data to identify one of several common technology diffusion or substitution models. Patterns to be identified include constant percentage rates of change (so-called “Moore’s Laws”), logistic growth (“S”- curves), logistic substitution, performance envelopes, anthropological invariants, lead/lag (precursor) relationships, and other phenomena. These quantitative projections have proven accurate in predicting technological and social change in thousands of diverse applications, on time scales covering only months to spanning centuries.

Invariant, or well-bounded, human individual and social behavior, and fundamental human agency and evolutionary drives, underlie technological change. In essence, humans and technology co-evolve in an ecological system that includes the local environment, our internal physiology, and technology that can be considered simply external physiology.

Carrying out a quantitative technology forecast includes selecting a strategically important technology, gathering historic data related to change 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 the natural characteristic patterns of technology change and diffusion.

QTF 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 take

on common patterns. The discovery of such a pattern indicates that a fundamental trajectory or envelope curve has been found and that reliable forecasts then can be made.

The quantitative forecasting techniques are, to use the words of mathematician and theorist Gregory Bateson⁴ “explanatory principles”, that is, their applicability is sufficient by their reliability for the purposes of modeling technology diffusion patterns and forecasting technology adoption. Many researchers have attempted to substantiate the commonly found patterns through application of systems 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 information theory, process ecology, systems theory, and complexity modeling, such as complex adaptive systems.

Several of the many techniques in quantitative technology forecasting are ideally suitable for projecting technological change and technology sustainability in early stage practicality and affordability studies are introduced here in more detail and illustrated with examples, including possible topics for space-related studies.

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 (see, for example, Malthus⁵). 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 next to the logistic (or so-called S-curve) to model technology diffusion.

In the late 20th Century, researchers in the United States such as Lenz⁶, Martino⁷, and Bright⁸, and others around the world [e.g., the very prolific Marchetti (see, for example, Marchetti⁹)] refined forecasting methods and showed that the logistic model was an excellent construct for forecasting technological change with virtually universal application for technology adoption and many other individual and social human behaviors. 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 that renders the logistic curve linear¹⁰.

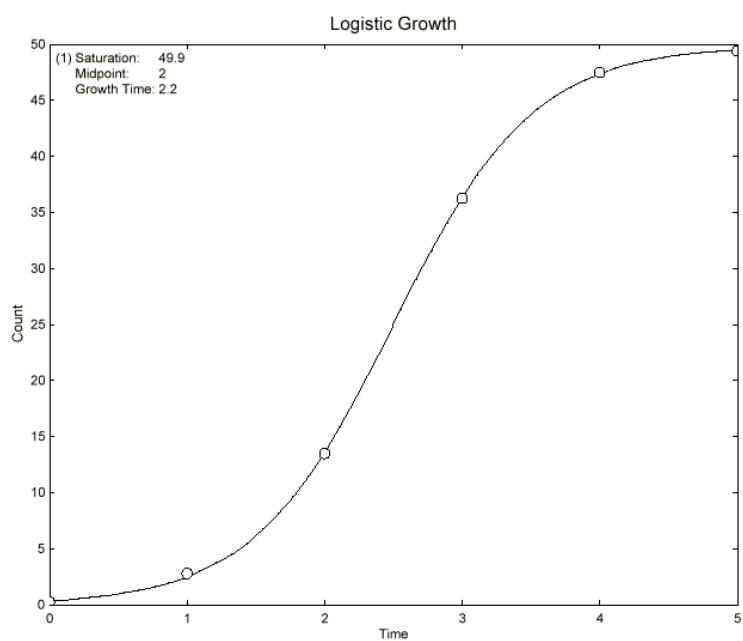


Figure 1. Ideal logistic growth curve (Adapted from Meyer, et al¹¹).

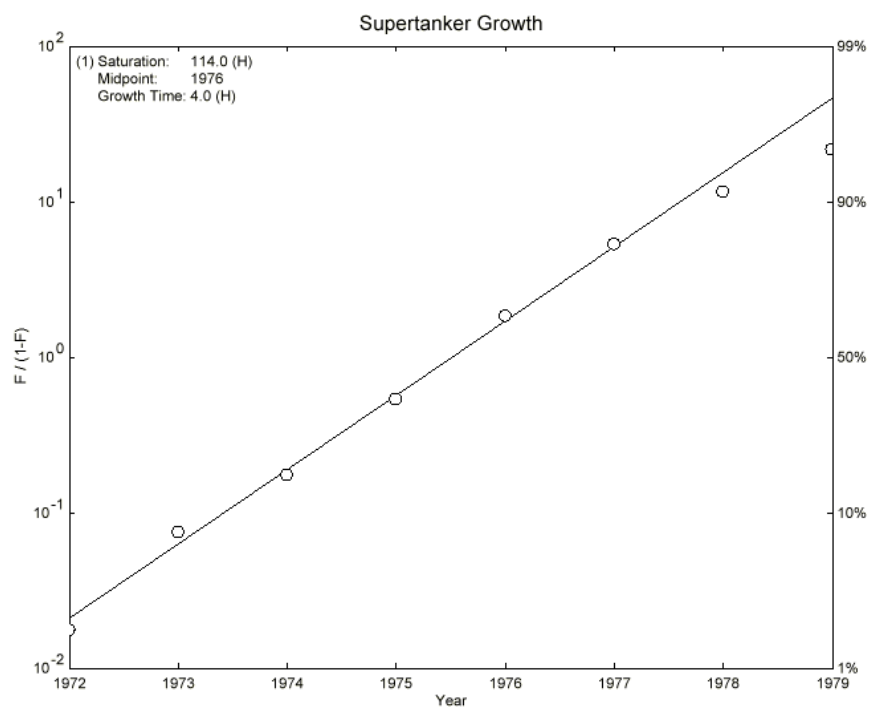


Figure 2. Logistic growth of the supertanker (Adapted from Modis¹²).

Figure 3 shows the growth pattern of a recent computer virus that infected computers on worldwide networks.

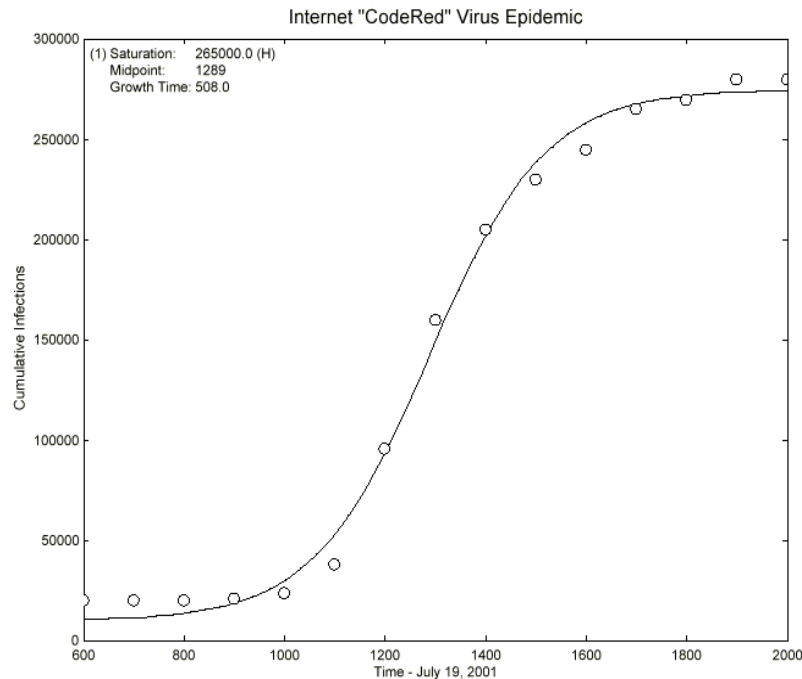


Figure 3. Logistic growth of a network computer virus (Data from Danyliw and Householder¹³).

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 the incumbent technology at some higher, but practical, performance level, humans tend to go about the changeover in a methodical way, managing to maintain equilibrium in the vast array of a culture's interacting and interdependent social, material, and economic systems.

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

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.

Figure 4 shows an example of the performance characteristic curve for transistor density on a microprocessor chip, the popular “Moore’s Law”. Figure 5 shows the performance envelope of industrial energy substitution, pointing to the high-efficiency fuel cell as the next candidate for leading energy conversion technology.

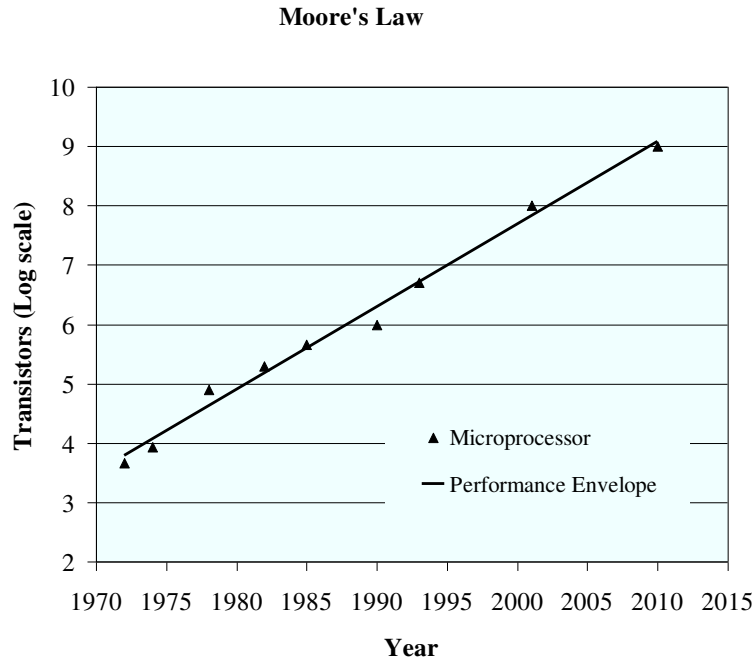


Figure 4. Moore’s Law - Performance envelope of microchip transistor density (Data from Intel Corp.¹⁴)

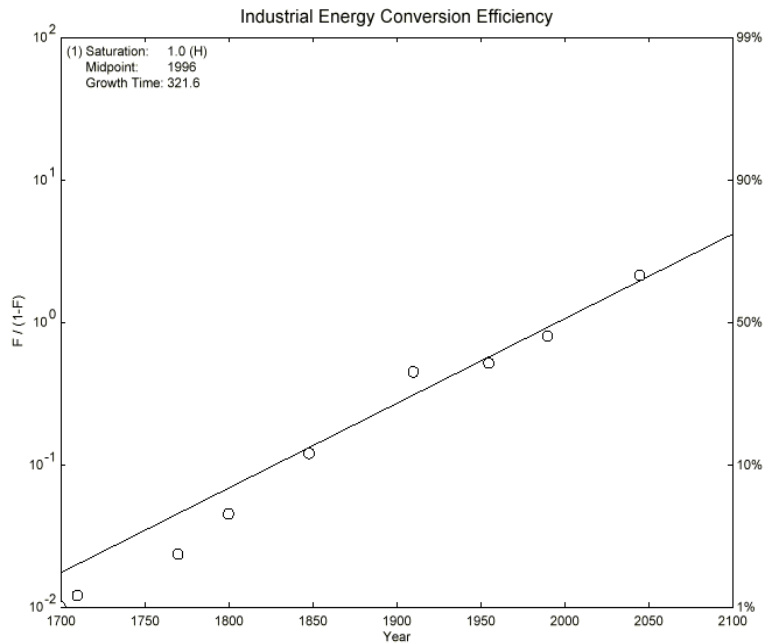


Figure 5. Performance envelope of industrial energy conversion technology, with projection to 2050 (Adapted from Ausubel and Marchetti¹⁵).

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 analyzed hundreds of technological substitutions in history and devised a method to graph the substitution patterns in linear fashion, thus giving us the popularly applied Fisher-Pry projection of technology substitution.

Figure 6 illustrates the typical logistic substitution pattern. Studies have shown this remarkable logistic substitution pattern in technologies as diverse as the substitution of automobiles for horses in personal travel and the substitution of latex for oil based paints. In the maritime industry, published reports show the logistic substitution of motor-over-steam-over-sail in ship propulsion technology (see Figure 7).

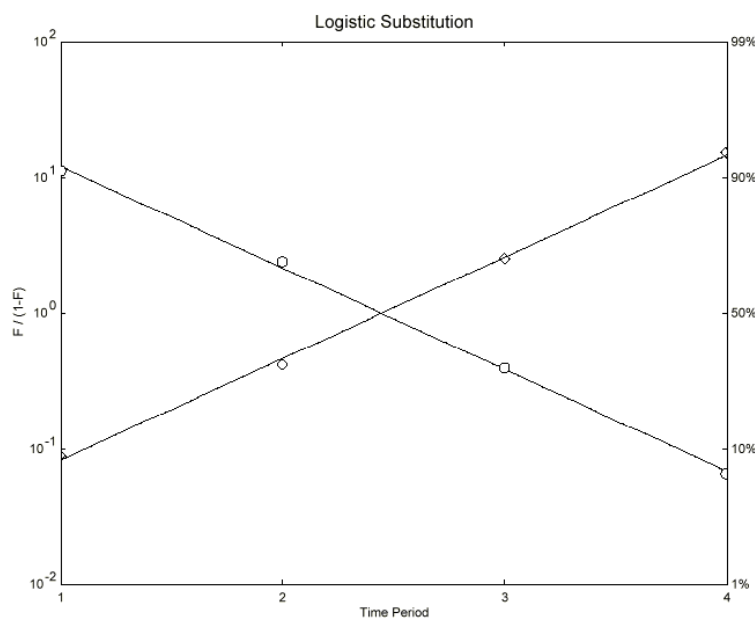


Figure 6. Typical logistic technology substitution (Fisher-Pry display format).

Precursor (Lead-Lag) Growth

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 usually linked in a steady lead-lag relationship (see Figure 8).

Studies have shown that the worldwide discovery of petroleum resources has led the production of oil by a fixed period over many decades (see Modis¹⁷). Studies have shown also that the diffusion in USA industry of networked desktop personal computers followed the same shape logistic trajectory as the precursor technology, stand-alone PCs (see Poitras and Hodges¹⁸).

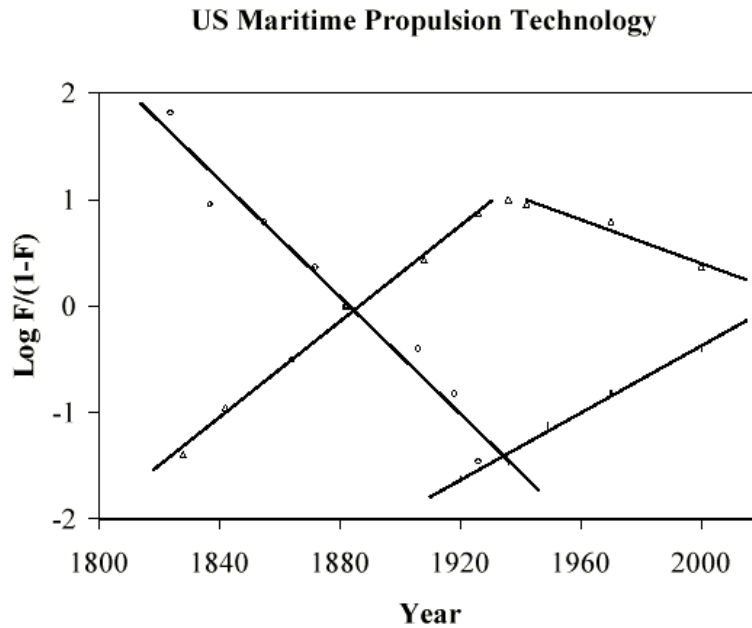


Figure 7. Substitution of US maritime propulsion technology (Adapted from Modis¹⁶).

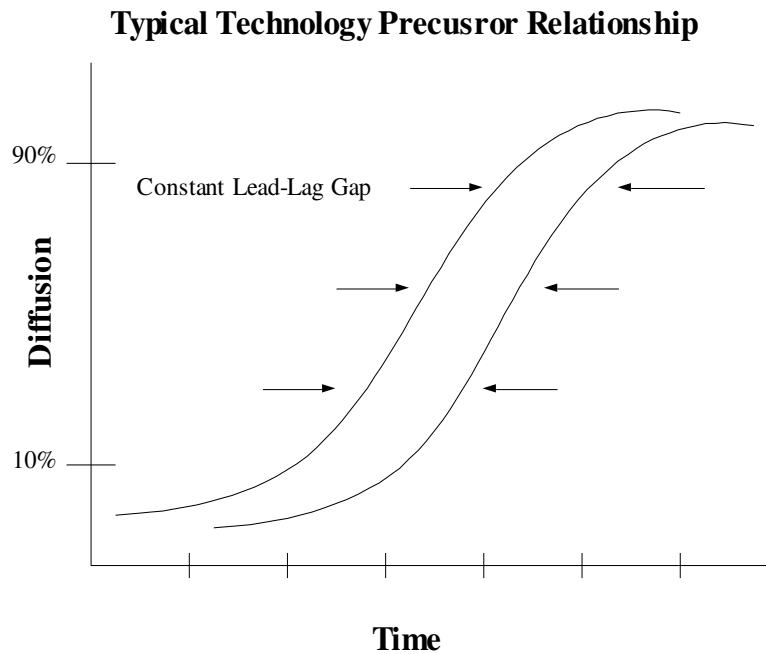


Figure 8. Constant lead-lag logistic relationship.

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 human behavior in many areas. 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. The anthropological benefits in applications of technologies can be viewed as artifacts of unchanging human behavioral preferences. As an example, Figure 9 shows the more or less constant accepted (and, by implication, engineered and designed) risk of death by automobile in the United States over nearly an entire century.

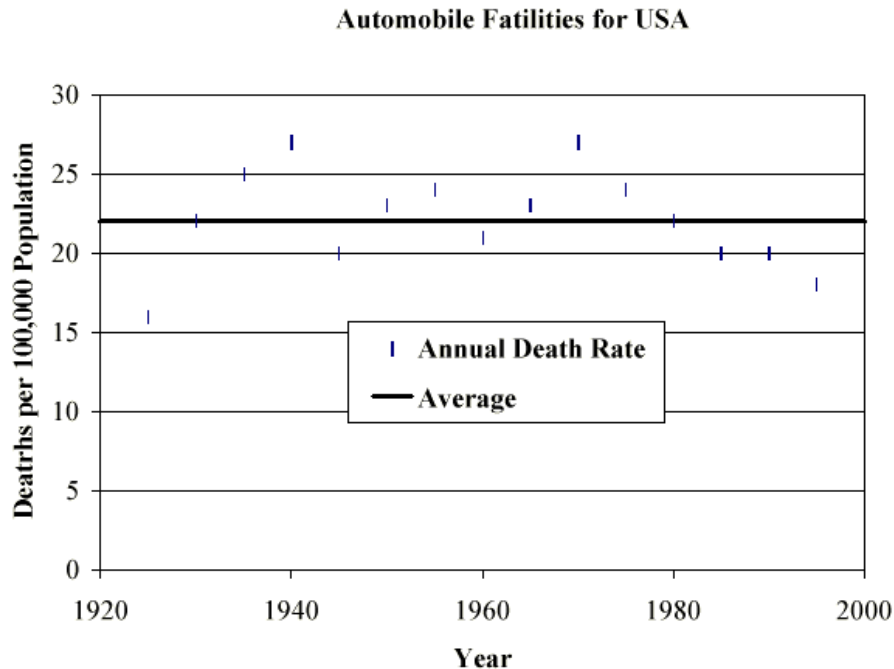


Figure 9. Risk of having a fatal automobile accident in the US (Adapted from Marchetti¹⁹).

Technology and Innovation Process

The concept of the ‘disruptive’ nature of innovation or technology has been popular in business and technology articles and books (see, for example, Christensen²⁰). The history of technological change, however, is shown to be a series of incremental changes or combinations of existing technology. While a new or overtaking technology might disrupt a business or business network, the technology itself, viewed historically and within a progressive, quantitative model can be shown to be – in retrospect or prospect – still only an incremental change. According to Marchetti, “Show me a ‘disruptive’ technology, and I will show you its logistic [growth] curve²¹”.

Also a popular story is that of the lone inventor tinkering in isolation to unveil to the world marvelous new inventions. The myth is not supported by the record of technological change. Inventions are born of a combination of human need and private (or collective) agency or ambition, and are cobbled together from known techniques and materials. Beginning with one technological platform, the directions of innovation are finite. One can alter the mass, or size, or

some other measurable performance criteria, but within a finite space. In fact, forty such directions have been identified by analyzing and identifying trends in patent claims and are used in a systematic approach or algorithm to problem solving and invention called the TRIZ method, from the Russian acronym for “Algorithm of Inventive Problem Solving”. (See, for example, Altshuller²²).

The TRIZ algorithm can indicate in what directions innovation can or will take place, providing insight and guidance to technology creators and users alike.

Technology Emergence

QTF techniques are especially useful after the chaotic sorting out of concepts and ideas in research and development stage, and after the technology as taken on a form and seen some absorption in its general use population. However, not every innovation or new technology emerges to become a commercial success. Research has focused on the earlier technology path from concept to product from a variety of approaches to better understand the process and to possibly accelerate or make the process more efficient, and perhaps more predictable.

The first attempts looked for linear or deterministic patterns but the chaos typical of early development, the unpredictability of the future states in which the technology will fill a need, and the extreme number and non-linearity of variables, made the task impossible.

Viewing technology progress in terms such as ‘survival’, ‘filling a niche’, or ‘sustainability’ led to thinking about technological change as an evolutionary process. This approach has not been an entirely satisfactory model still, for various reasons, but mostly because technologies have no ‘agency’ as do living things²³.

Some of the latest thinking suggests a process ecology approach to technology emergence and change. Ecology is more a study of process than organism. That technological change can be predicted, as, for example, along a performance trajectory, yet the technological form might not be, process ecology modeling shows promise to model the emergence, growth, and survival of innovation and technological change²⁴.

Sample Technology Forecasts

Us Navy Destroyer Warship

The first problem considered was the future of shipbuilding resource allocation to the US Navy class of warship, the destroyer, in the context of evolving national defense needs and seafaring technologies. Analysis involved plotting the cumulated destroyer launches per date from the warship’s arrival in the late 1890’s through its present production. Figure 10 shows the raw data and the best-fit logistic curve. An excellent fit to the common logistic diffusion pattern resulted, with two above-the-trend spikes reflecting intense production rates during each of the two world wars. The logistic pattern flattens out beginning around 1975. As seen in Figure 11, where the Fisher-Pry transform renders the curving logistic pattern linear, the threshold of 90% of final or saturation growth had been attained by around that year. This indicates that we are well into the last stage of new destroyer production. Now that we are nearly thirty years out from the onset of decreasing cumulative growth, any new spike in growth is extremely unlikely. The clear logistic

diffusion pattern found is typical of other historical comings and goings of warships and warship classes (see, for example, Marchetti²⁵).

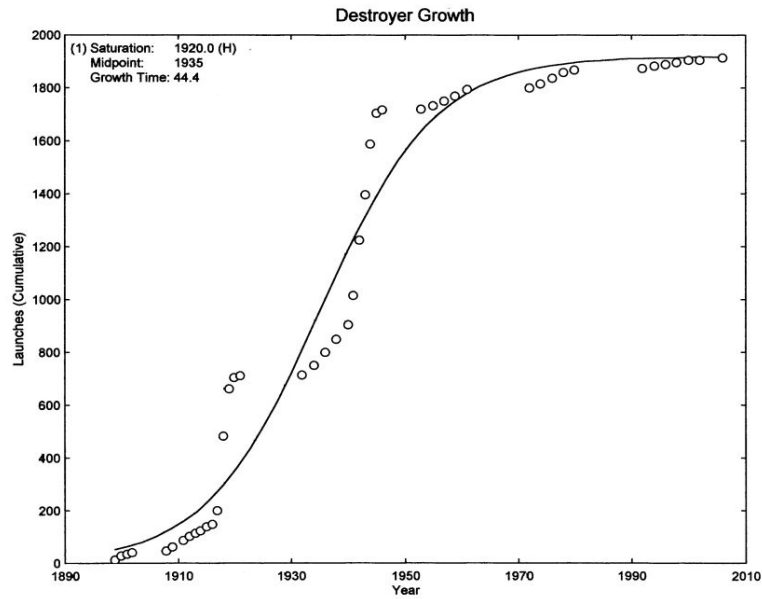


Figure 10. Cumulative Production of US Navy Destroyers (Data from US Navy).

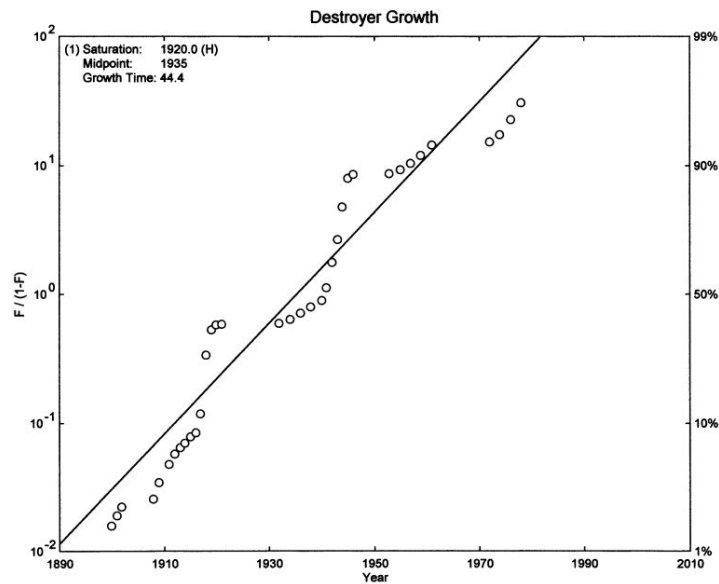


Figure 11. Fisher-Pry transform presentation of the same data used in Figure 10.

Not lost in this analysis is the analogy of the evolution of species with the idea of considering destroyers as a species. The destroyer filled a niche, so to speak, and grew in a larger ecosystem

of ecological processes and evolutionary change encompassing global power dynamics and major technological advances. As species do in nature, the niche affected local niches, and by various feedback and self-modifying loops the niches affected higher levels of organization in the ecosystem. This emerging interdependency drove the co-evolution of several species of warships, warfare, and war strategy, even on a global scale.

Species come and species go in the complex and chaotic world of natural selection, ecological change, and expanding diversity. These process and systems are becoming better understood and modeled, and the future of these studies should shed more light on the ‘lives’ of warships and other complex technological platforms and systems.

Commercial Lighting Efficiencies

A forecast of the efficiency of commercial lighting technology is presented (see Figures 12 and 13) by assuming continued logistic growth in the adoption of increasingly efficient lighting sources. The logistic, or s-curve, pattern is typical of other historical progressions of efficiencies, such as in the production of ammonia and in energy converting prime movers (see, for example, Marchetti²⁶). “Moore’s Law”, which has accurately projected the doubling of microprocessor chip density every 18-24 months for several decades, is a popular example of this phenomenon.

The data for the years 1800 through 1950 were taken from Marchetti. The efficiency of 160 lumens/watt by 2007 was taken from Schubert²⁷. The balance of the projection through 2100 was made by fitting the logistic function through the Marchetti and Schubert data. An excellent fit is achieved for the saturation level of 200 lumens/watt. This efficiency is about half the maximum theoretical efficiencies of known LED technologies (see, for example, Savage²⁸). Through approximately 10-90 percent of its growth, lighting efficiency doubles about every 25 years.

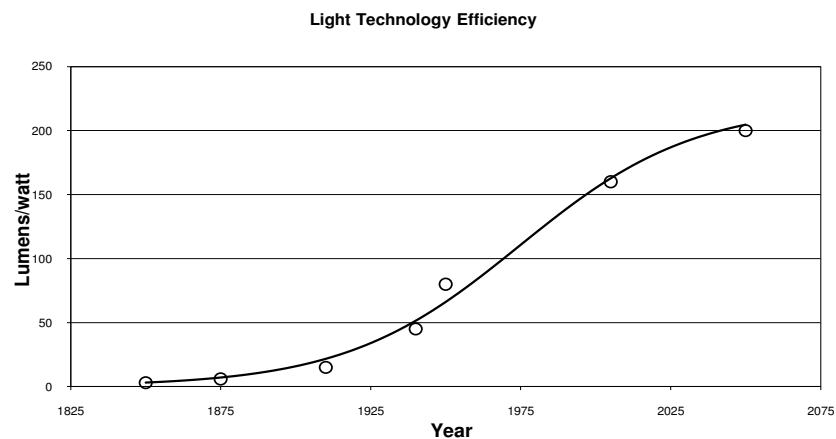


Figure 12. Logistic growth of lighting technology efficiency.

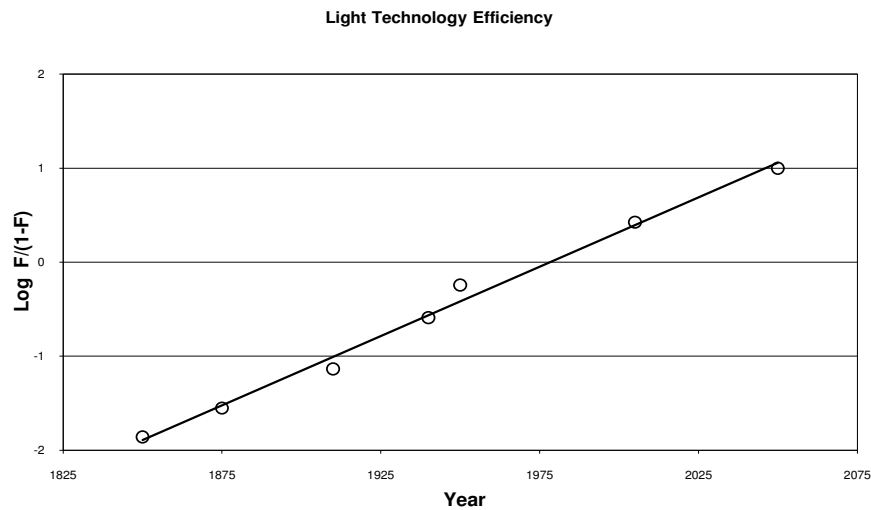


Figure 13. Fisher-Pry transform presentation of the same data used in Figure 12.

Technological Literacy and Career Guidance

The author shared teaching in a Professional Development course to undergraduate engineering and engineering technology major midshipmen at a US maritime academy. The goal of the course segment on technology forecasting was to encourage students to consider not only the business status of a future employer but also its technological status.

Students were introduced to the fundamentals of technology change and substitution, as outlined in this paper. The students were encouraged to identify and study the trends of technology in their own career paths and to be strategic in their choice of employers. Students were introduced to the levels of technological risk in job choices, e.g., a high-employment, mature-technology company might be a greater long-term risk than a low-employment, new-technology company. The level of career technological risk was a new concept to them, but they were given means to begin to assess the technological risk in future employment, and to consider the amount of risk they were willing to accept.

Conclusion

Understanding technology change and how to influence the process has been identified as a critical societal problem, and efforts to define and increase technological literacy have been underway as an approach to solving the problem. Technological literacy cannot be complete, therefore, without an understanding of major processes of technological and social change. Knowledge of means to understand and project paths of technology and innovation would constitute important content in a technology literacy program.

This paper has presented an overview of the major processes describing technological change identified through quantitative technology forecasting techniques, and provided examples of the

author's experiences researching and applying the methodologies. The author shared his experience introducing the concepts and sample studies in discussions of career and personal technology choices with undergraduate students in introduction to engineering and engineering technology courses.

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