AC 2011-1979: IMPROVING TECHNOLOGY LITERACY CRITERIA DEVELOPMENT

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Improving Technological Literacy Criteria Development Through Quantitative Technology Forecasting

Abstract

Definitions or proposed requirements of technological literacy change as technologies and their applications in the workplace and social interaction diffuse and evolve in complex socio-technical ecologies. An historic problem encountered by technological literacy advocates is this environment of many moving targets, making the specification of technological literacy criteria and objectives in education a very difficult task. Just when the criteria are defined and proposed, the technology evolves and the criteria are rendered obsolete.

An example of this challenge can be found in the history of the adoption of computer programming languages. At separate times, it was considered critical that all students in secondary school should be able to program in BASIC, and all undergraduate engineering students be able to write in FORTRAN, and that all business students be able to program in COBOL. These languages are used in only niche environments, if not altogether rare, today, and certainly are not in any way critical skills expected in the common workplace.

Some technologies emerge, peak, and whither quickly, i.e., long before the educational need or level can be addressed. Some technologies diffuse over relatively long periods of time, such that it is difficult to target the level and timing of literacy requirements. Still otherwise promising technologies never reach a significant substitution level, and need not be considered, after all, in a literacy criteria study. The establishment of criteria for assessing technological literacy then, now, and in the future, could significantly be better targeted and more effective if trajectories of diffusing technologies and their applications were available.

New techniques in forecasting technology change have given fresh perspectives on acceptance criteria and adoption rates of new technology. Quantitative technology forecasting studies have proven reliable in projecting technological and social change using relatively simple models such as logistic growth and substitution patterns, precursor relationships, constant performance improvement rates of change, and identification of anthropologically invariant behaviors.

This paper presents quantitative technology forecasts of the emergence, growth and projected future saturation levels of several computationally and numerically intensive analytical technologies – computation fluid dynamics, modeling and simulation, and finite element analysis. The trajectories are compared to the emergence and diffusion of the response of academia to provide curricula and course education in these technologies so that students are technologically literate in the use of these technologies upon graduation to research and industry.

The results provide insight into the lead-lag time relationships of these computational technologies and their co-evolved literacy components. General conclusions on the advantages of including technological trajectories in technological literacy criteria development derived from the results of this research are given.

Introduction

Literacy in technology, including knowledge of technological and social change, has been cited in various organization and research publications[1, 2, 3] as a 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 reliably 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 and related social changes 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.

In this paper, the process of using QTF techniques to characterize the growth and diffusion of computationally and numerically intensive analytical technologies [Finite Element Analysis (FEA), Computational Fluid Dynamics (CFD), Finite Difference Methods (FDM)] is detailed. This paper presents the results of testing the hypothesis that these computational tools would grow along commonly found diffusion patterns. If the hypothesis were supported, such patterns would give insight to the future development of the growing use of modeling and simulation (M&S) tools and the industry rapidly developing founded on their use. If reliable trajectories could be established, these would provide new information for strategic resource investment, especially with regard to the timing and diffusion of the need for M&S technology skilled, and M&S technology literate, workforce in the future.

These results could act as early proxies to support more QTF studies in other areas of technological change critical to strategic national efforts at defining, and raising, technological literacy.

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. (For further discussion of the broadening understanding of the ubiquitous technological nature of human endeavors, see Altshuller[4], Arthur[5], and Kelly[6]).Under this broad definition, not only are tools, materials, communications and other obvious technologies included, but so are software, accounting, the law, and other human activities. Studies have shown that the emergence, diffusion, and obsolescence of all these categories of human creations follow rates of adoption and rates of change in performance that share 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 can be said to 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 Bateson[7] "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 techniques in quantitative technology forecasting are ideally suitable for projecting technological change and technology sustainability in early stage practicality and affordability studies. The technique used for all studies in this paper is logistic growth projection.

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, Malthus[8]). 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 Lenz[9], Martino[10], and Bright[11], and others around the world, e.g., the very prolific Marchetti (see, for example, Marchetti[12]), 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 linear[13].

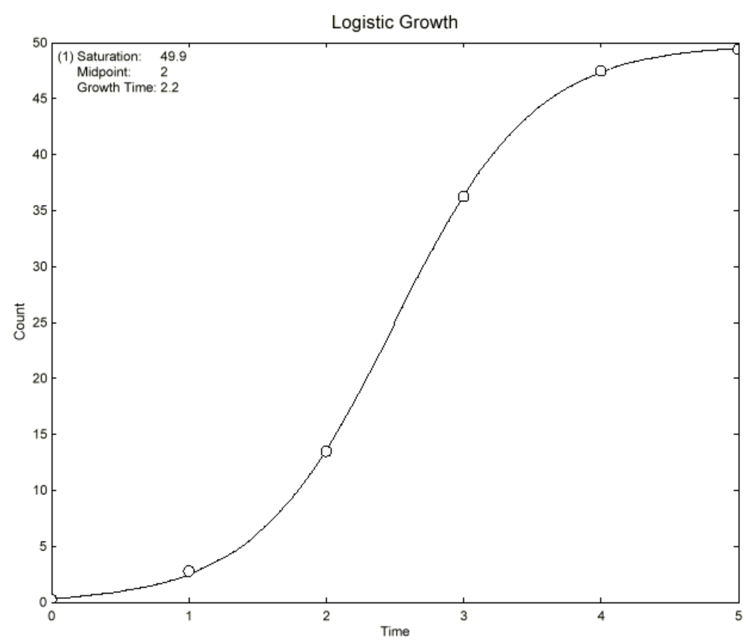

Figure 1. Ideal logistic growth curve (Adapted from Meyer, et al[14]).

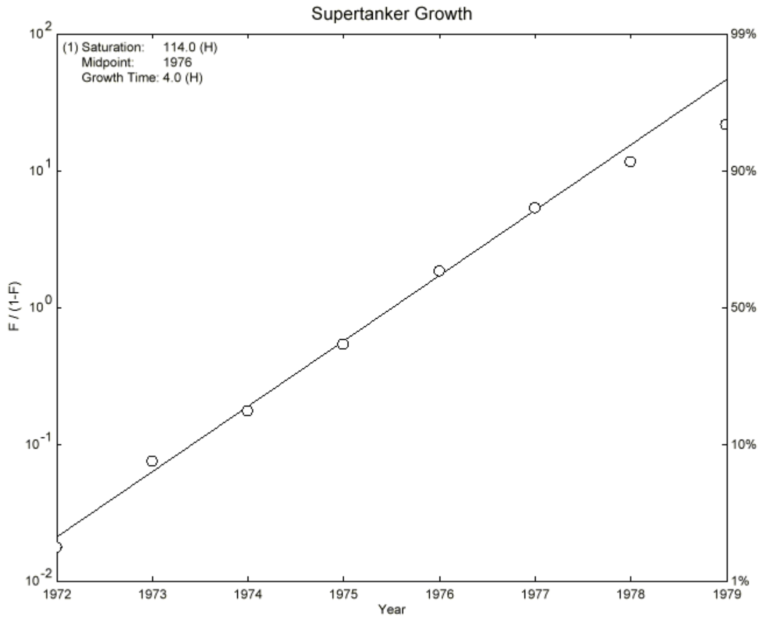

Figure 2. Logistic growth of the supertanker (Adapted from Modis[15]).

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

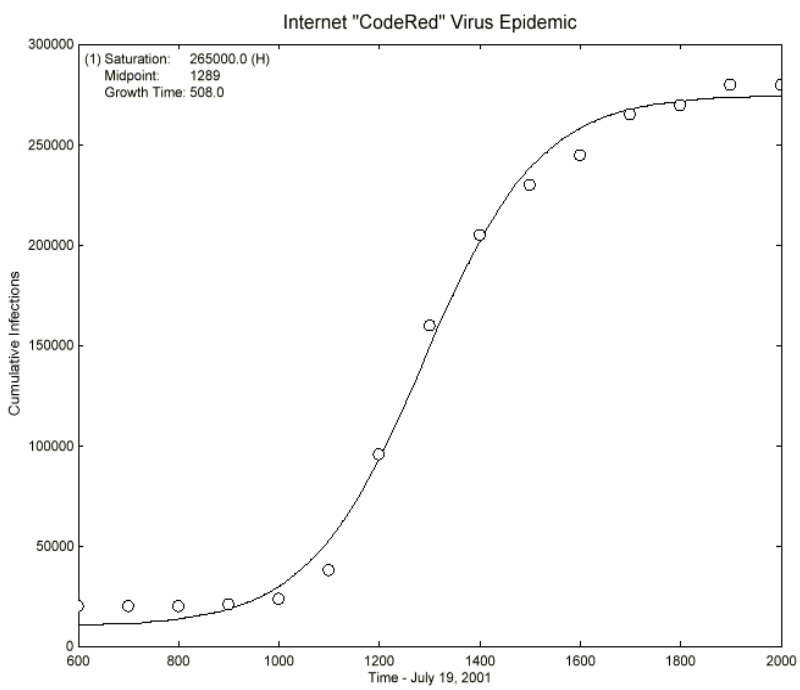

Figure 3. Logistic growth of a network computer virus (Data from Danyliw and Householder[16]).

Analysis and Results

Research and Methodology

In preparation for a workshop on strategic technology management for consultants, entrepreneurs, and researchers in the growing modeling, analysis, and simulation (M&S) industry, the author undertook sample studies of trajectories in computationally intensive engineering tools. The idea was to provide for the participants one or more QTF-based projections of M&S activity[17].

Bibliometric studies are one approach to characterizing the growth and diffusion of a technology. These studies include data mining comprehensive publications databases for specific instances of public communication of the select technology of interest. Porter[18], for example, provides a good general introduction to procedures and uses of bibliometric analysis.

Comprehensive bibliometric analyses were undertaken including academic publications with titles, subject keywords, and abstracts containing the technologies of interest: Finite Element Analysis (FEA), Computational Fluid Dynamics (CFD), and (subsequent to the workshop) Finite Difference Methods (FDM). Attempts were made to eliminate duplicate publications 'hits' and papers with irrelevant content but captured nonetheless by the search engines provided by the databases.

The results for FEA and CFD, and later FDM were as hypothesized; the growth and diffusion of these numerical methods could be characterized quite well by logistic functions. Figures 4, 5, and 6 provide results of these studies[19, 20]. All plots so noted were prepared using the Loglet 2 software program developed at the Program for the Human Environment, Rockefeller University[21]. The gray areas in the plots are the 10% confidence intervals of the projections.

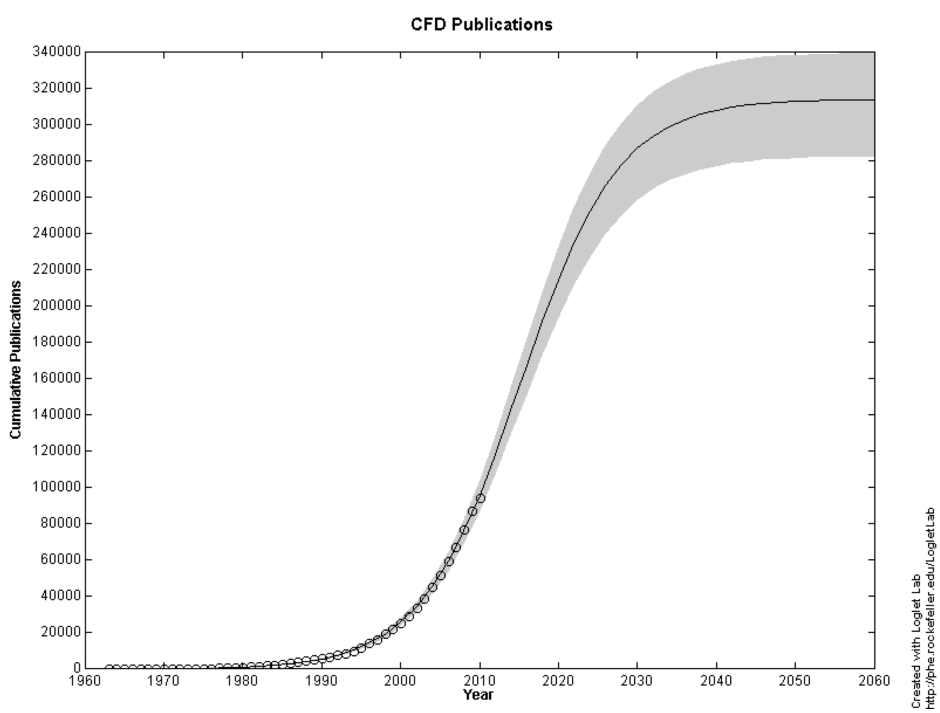

Figure 4a. Logistic growth of CFD Publications

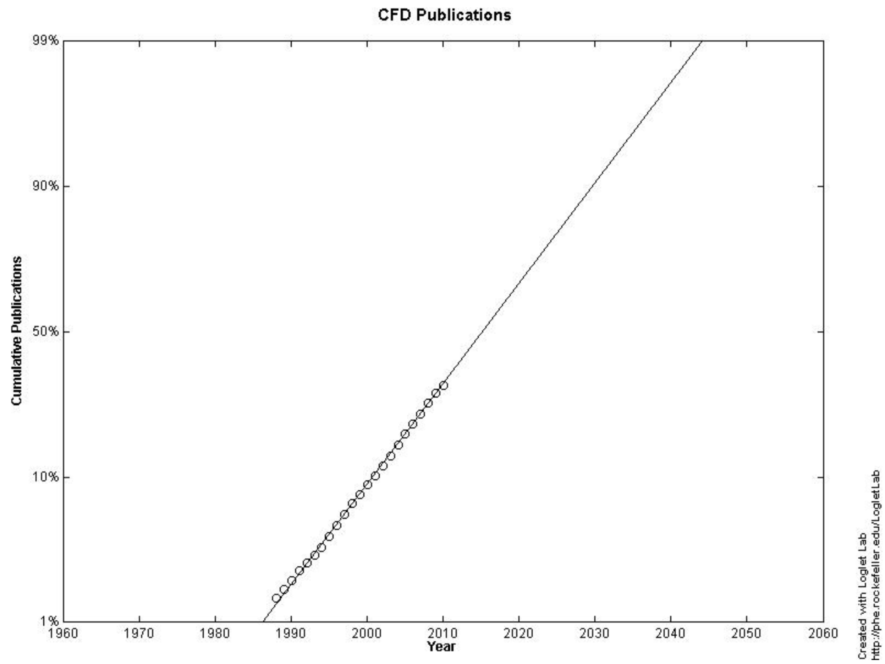

Figure 4b. Logistic growth of CFD Publications – Fisher-Pry Transform

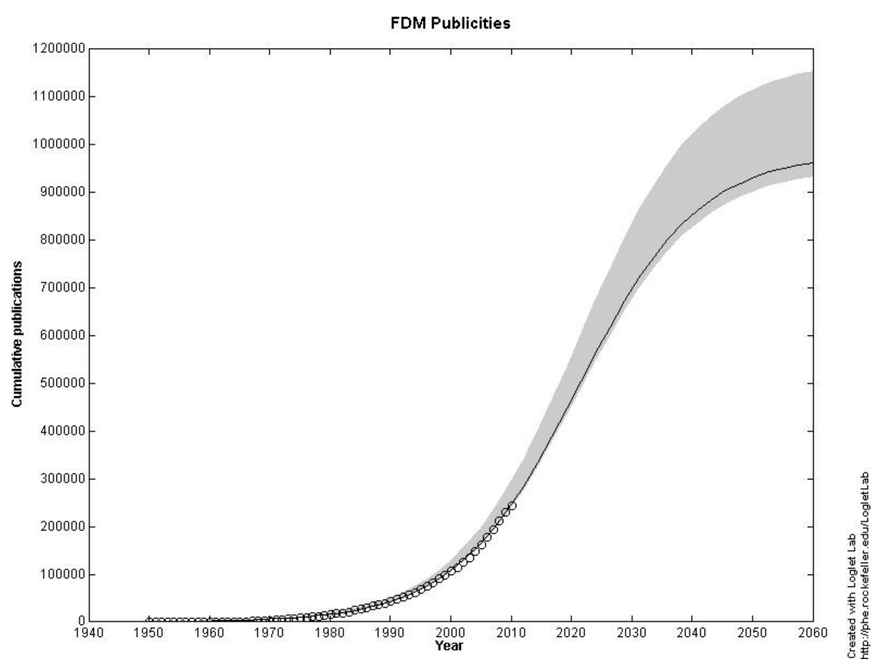

Figure 5a. Logistic growth of Finite Difference Method publications

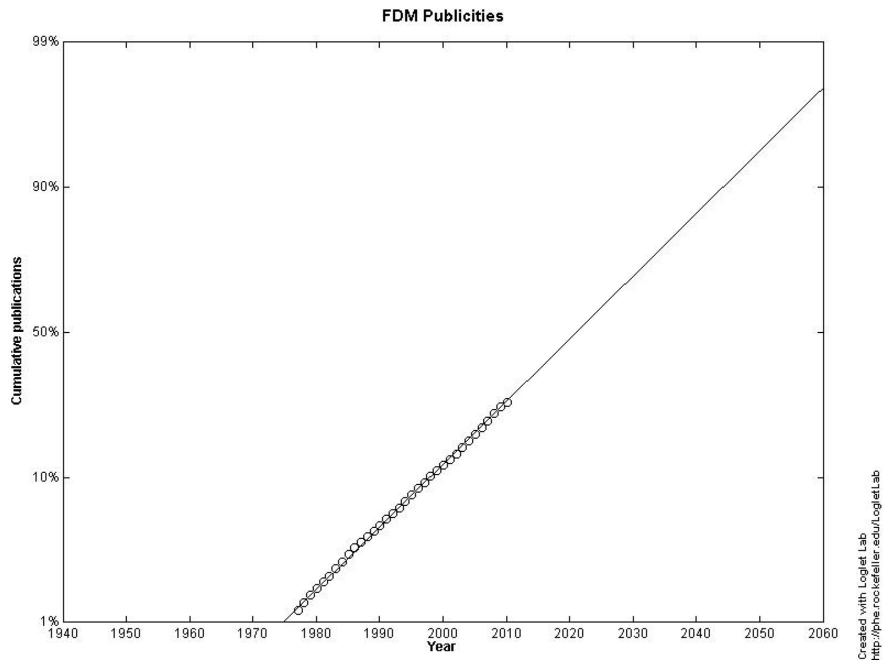

Figure 5b. Logistic growth of Finite Difference Method publications – Fisher-Pry Transformation

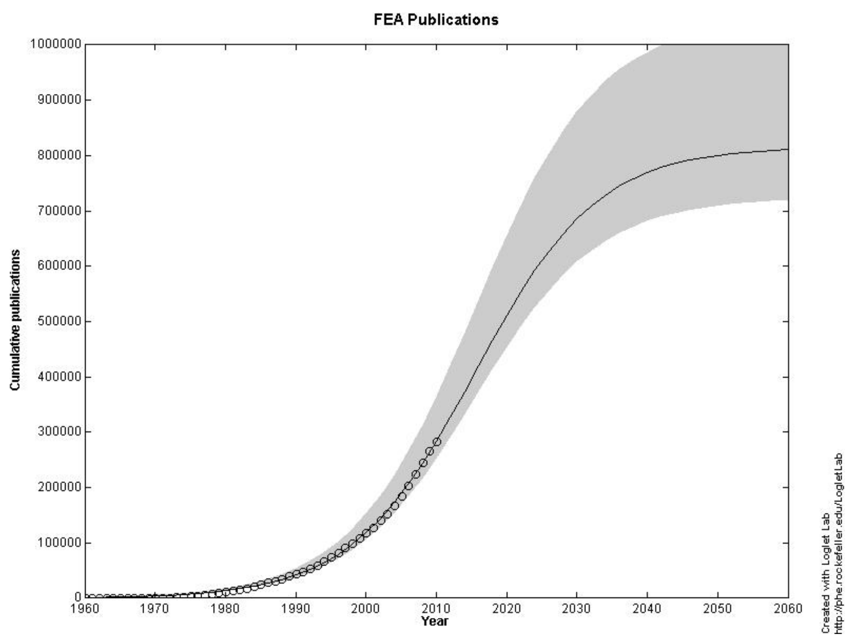

Figure 6a. Logistic growth of Finite Element Analysis publications

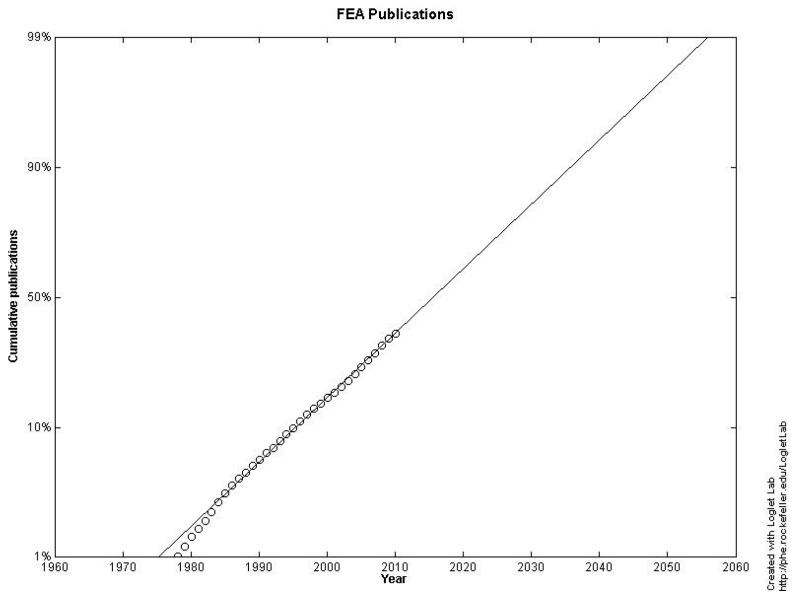

Figure 6b. Logistic growth of Finite Element Analysis publications – Fisher-Pry Transformation

Analysis of FEA, CFD, and FDM growth

In depth analysis of the reliability of logistic projections was undertaken by Modis[22]. Their research shows that when data are provided up to the 30% diffusion level of a trajectory, the projection to 90% will be within given by 10% confidence level. The projections of FEA, CFD, and DFM all show diffusion above 30% and the reliabilities deduced by Modis can be assumed.

Analysis of FORTRAN growth

Having found the selected methods less than 50% diffused, the author investigated the diffusion of an engineering numerical methods tool that he had considered mature and would yield greater than 50% diffusion: the FORTRAN analytical software program. Figure 7 shows again the good characterization of growth provided by the logistic model.

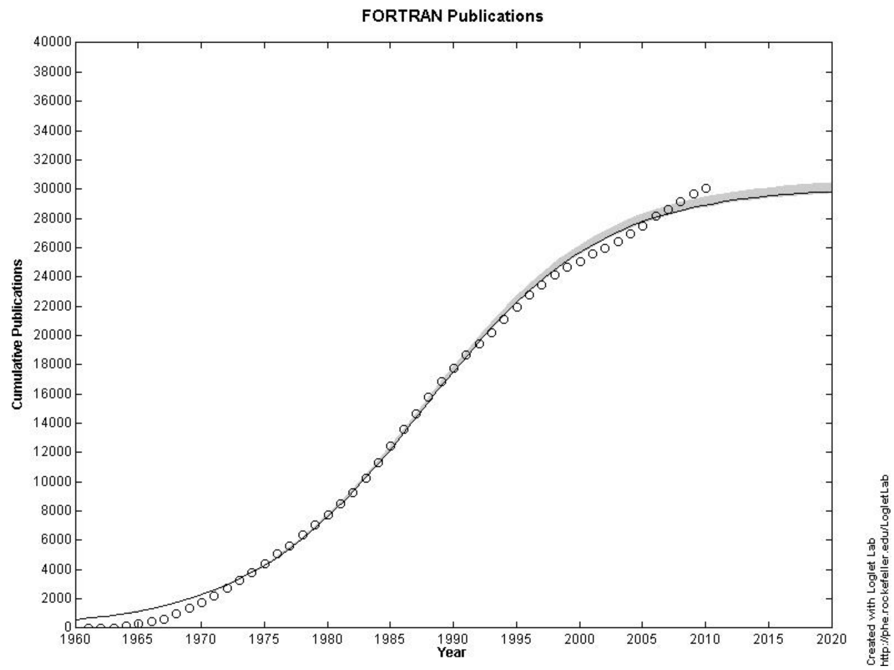

Figure 7a. Logistic growth of FORTRAN publications

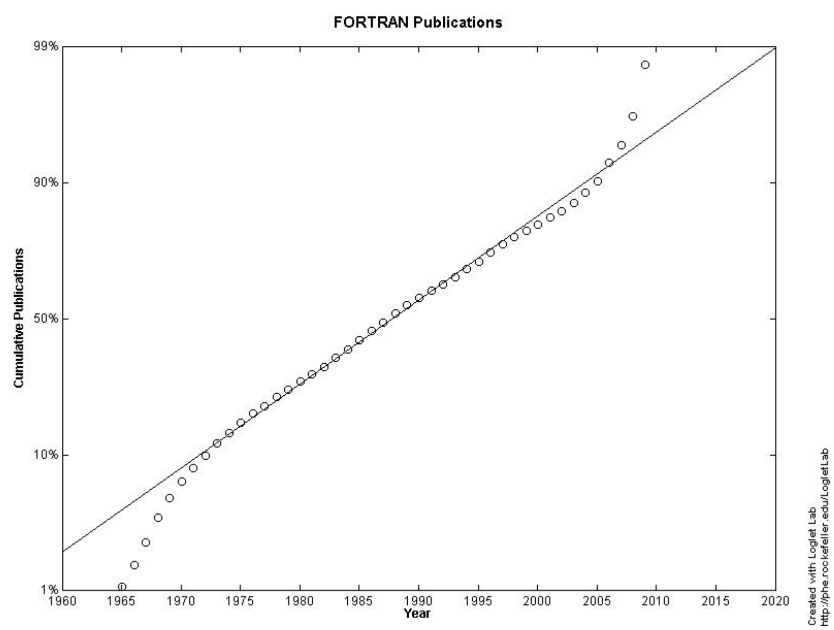

Figure 7b. Logistic growth of FORTRAN publications – Fisher-Pry Transformation

<u>Analysis of M&S growth</u>

Finally, M&S growth was analyzed. Figure 8 shows that M&S methodology is in its early stages of growth. M&S is estimated by logistic curve fitting to be only 10-15% along its trajectory life trajectory, and at this level the reliability of long-term (90% and above) growth is not as reliable as was found with FEA, CFD, or FDM.

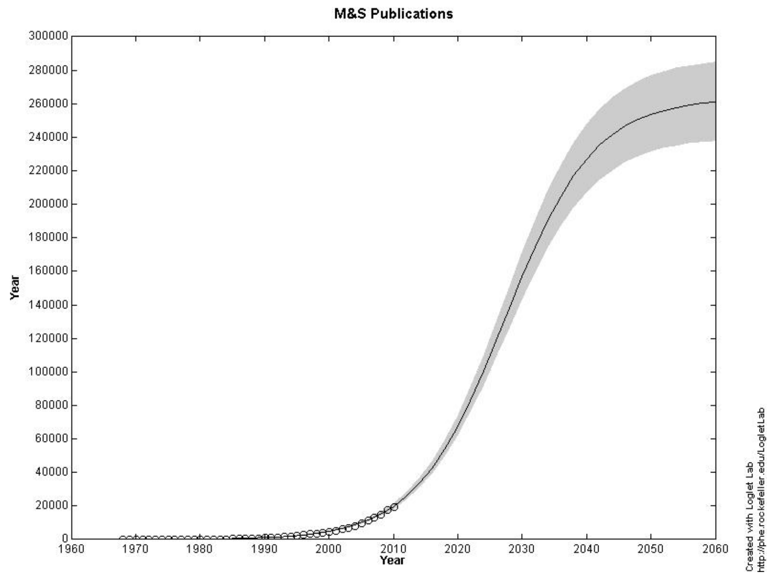

Figure 8a. Logistic growth of M&S publications

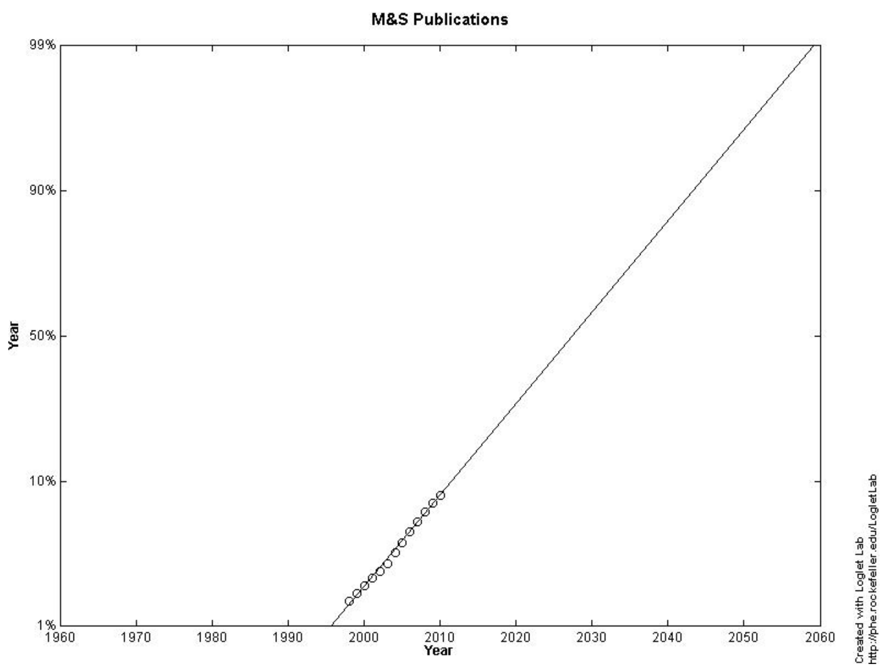

Figure 8b. Logistic growth of M&S publications – Fisher-Pry Transformation

Figure 9 shows a composite graph of the four (FEA, CFD, FDM, M&S) growth patterns normalized to levels reached in 2010. Note that FEA and FDM have similarly shaped curves, as compared to CFD and M&S, also having similar curves. This is to be understood as FEA and DFM are fundamental methods on which progress in higher-level applications such as CFD and M&S methods are based.

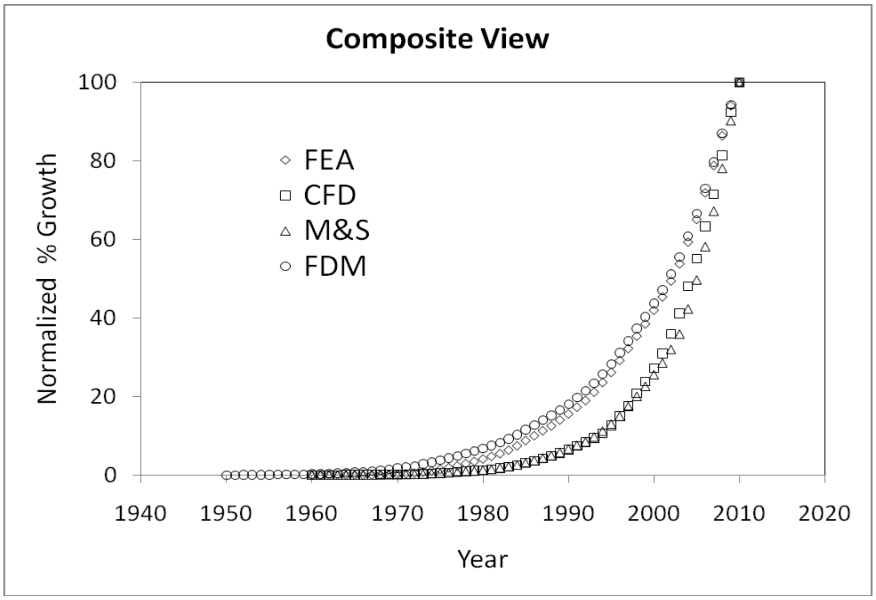

Figure 9. Composite view of growth patterns, normalized to 2010 level

Implications for Technological Literacy

<u>Research and Methodology</u>

The hypothesis that the growth in the select technologies could be characterized as logistic in nature was strongly supported. The larger purpose of the study, however, was to consider the use of such information in improving technology literacy.

The author endeavored to match events or trends in commercialization and education of the technologies to try to identify any timing or diffusion pattern commonalities among the select samples. The following were considered as good examples of events and trends common to the development of technologies such as the numerical methods tools investigated in this study:

- Text book publications
- Commercial products
- Skilled employment
- Industry standards
- Patents, trademarks, etc.
- University course offerings
- University course enrollments

As this study was undertaken with no external funding, extensive research that would have included contacting commercial publishers, academic text publishers, consultants, software developers, product and service vendors, etc., was not possible. It is not impossible that accurate records of university offerings on courses in the select technologies, or student enrollments, sufficient to characterize trends in education, are available, but their unearthing would take significant time and expense. Two approaches were taken to try to achieve correlation between industry adoption and scholastic adoption of the emerging and diffusing numerical methods studied.

Research and Education Trajectories Correlation

To attempt to correlate the logistic growth of these technologies with education trends, to then assess the implications for the use of QTF techniques in projecting technology literacy requirements, for this limited budget study, data representing 'low hanging fruit' was considered. The chosen source was the online catalogs of the Library of Congress that list annually published books with the subject matter in the title. It was expected that the catalog listings might serve as a reasonable proxy for more comprehensive data on developments in education (literacy) in general in the technologies of interest.

Analysis of FORTRAN

Figure 10 shows the logistic growth of the publication of FORTRAN texts analyzed in this way. FORTRAN was the premier programming language of multiple college courses for many years in the USA, but today is rarely taught as a language. Its logistic trajectory is nearly complete, as seen in the total number of publications (Figure 7) and the end of book publishing (Figure 10).

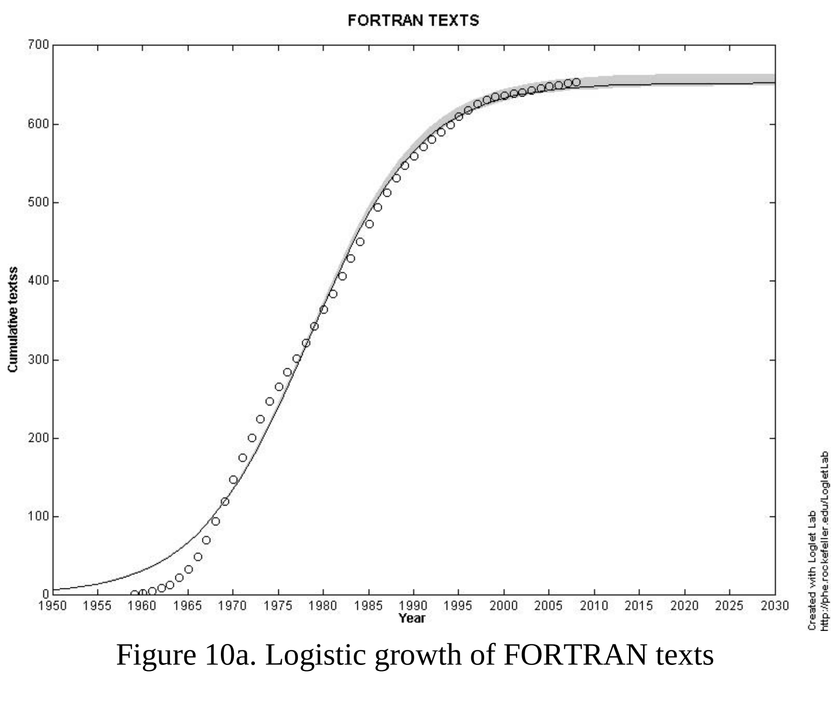

Figure 10a. Logistic growth of FORTRAN texts

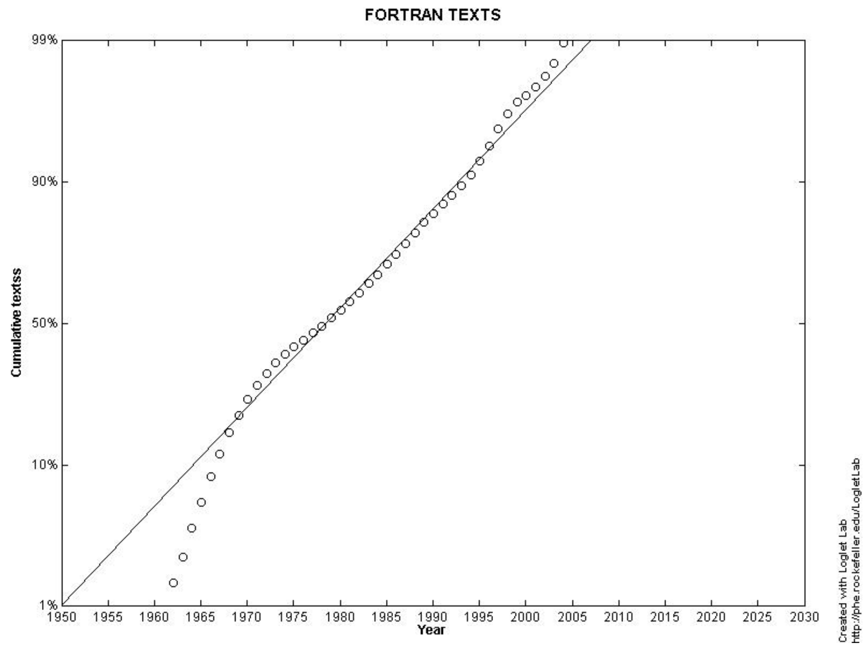

Figure 10b. Logistic growth of FORTRAN texts – Fisher-Pry Transform

Figure 11 shows concurrent plots of FORTRAN academic publications and FORTRAN texts. There appears a fairly constant lead-lag relationship where books lag publications by about 10 years.

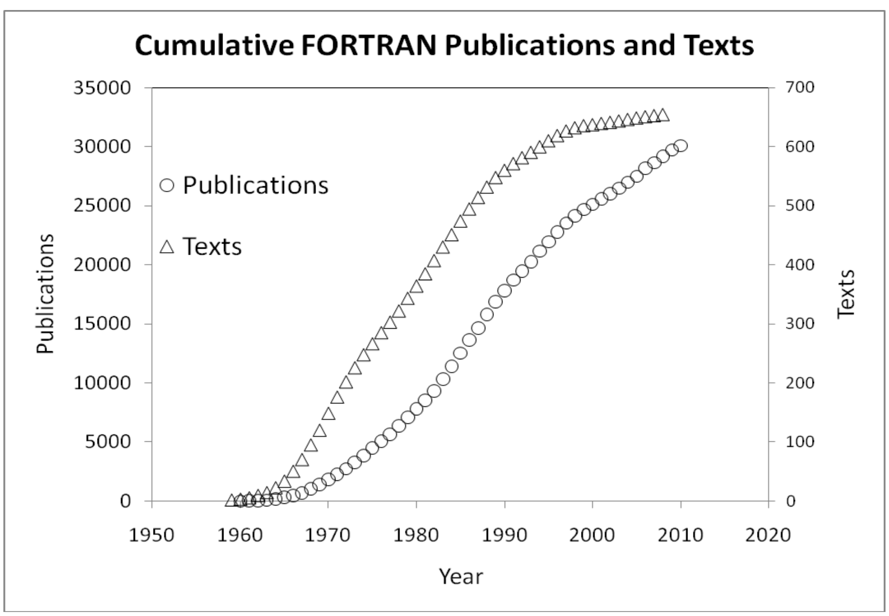

Figure 11. Lead-lag relationship of FORTRAN publications and texts

Looking backward, as a precursor to looking forward in the emerging technologies studied, it is possible to have anticipated the FORTRAN text and publications trajectories after the first 30% of growth (the level based on projected saturation levels). With this information, and other empirical data such as educational and commercial diffusion of the tool, we could have projected:

- Estimates of the shift from learners literate in developing the FORTRAN code, to learners primarily literate in applying the FORTRAN language to problem solving
- Estimates of the number of such skilled workers need, and when they would be needed
- Estimates of the time and rate of the substitution of more preferred software (those more easily learned, more easily used, more efficient in arriving at solutions, more flexible in applications, etc.) and other high level data manipulation and graphic display tools technology

A study of the life of FORTRAN, its early advantages and later disadvantages as compared to competing and ultimately displacing software, would be an interesting read.

Analysis of FEA, CFD, and FDM

Book publishing in FEA, CFD, and FDM did not show classic common lead-lag relationships between academic publications and commercial book publications, as was found in FORTRAN, and might be expected. The time lag between the two types of publications was obvious early on in the life cycle where text growth lagged scholarly publications. As did FORTRAN, CFD showed a pulse of book publishing shorter than academic publishing. This result is intuitive: academic publishing would emerge well before books are written, and predictably go on for a short period of time after the last text is published and the functional expansion of the technology is exhausted. However, FEA and FDM results did not follow this model. FEA books project a longer life and later mid-point in time than their academic counterparts. The linear growth of FDM texts, at least as found at the Library of Congress, limited applicability of the logistic analysis. More comprehensive text publication data would improve the analysis and results.

Figures 12 through 14 present findings of CFD, FEA, and FDM text publishing analyses.

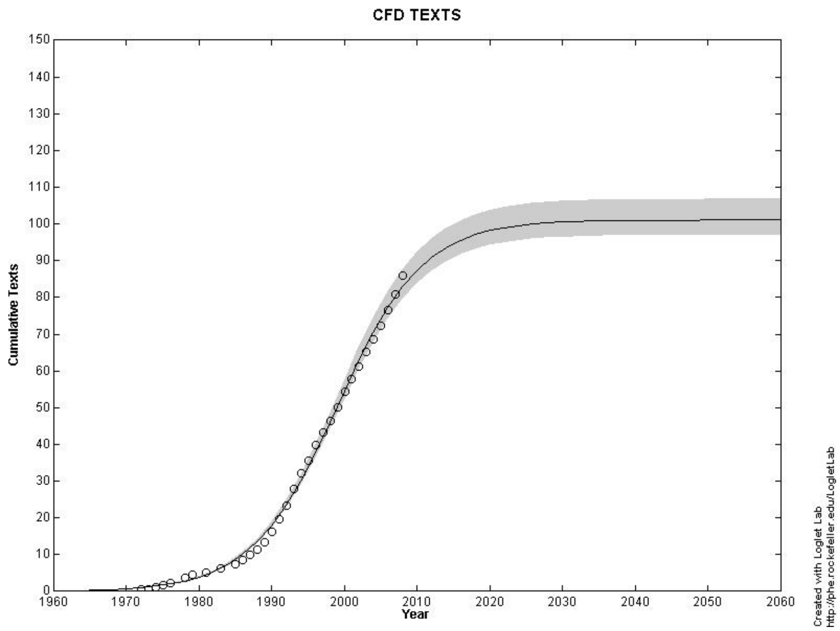

Figure 12. Logistic growth of CFD texts

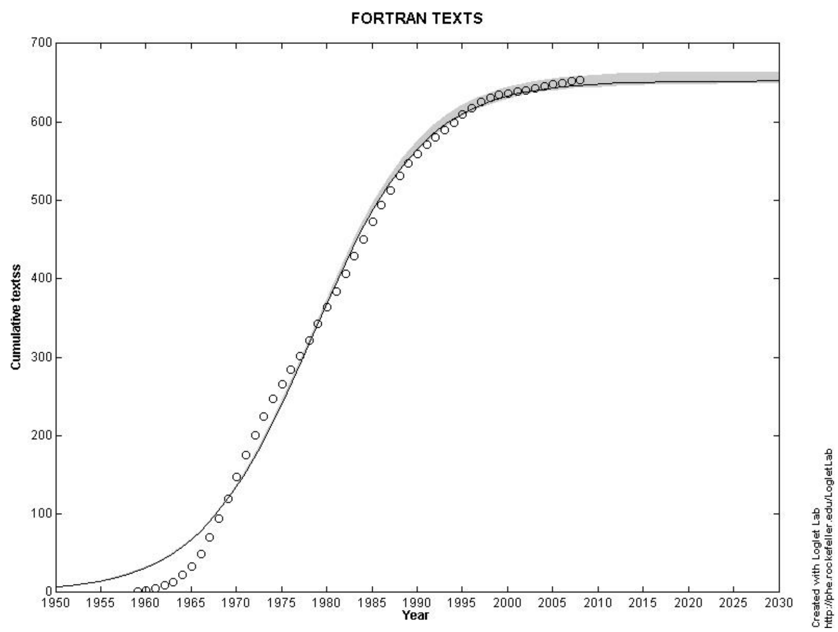

Figure 13. Logistic growth of FEA texts

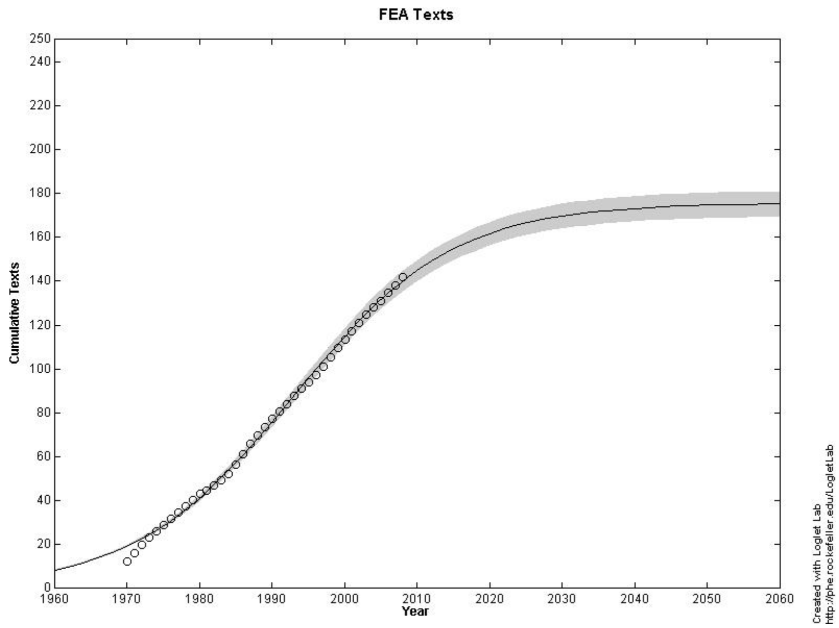

Figure 14. Logistic growth of FDM texts

<u>Analysis of M&S</u>

M&S publishing followed the intuitive supposition that texts would be published logistically and would lag consistently academic publications. Figure 15 shows the estimated logistic growth of M&S texts, and Figure 16 shows the combined results of publications and texts in the current emerging time period. Note, however, that trajectories of text publication point to a longer period of growth and a nearly coincident mid-point of growth.

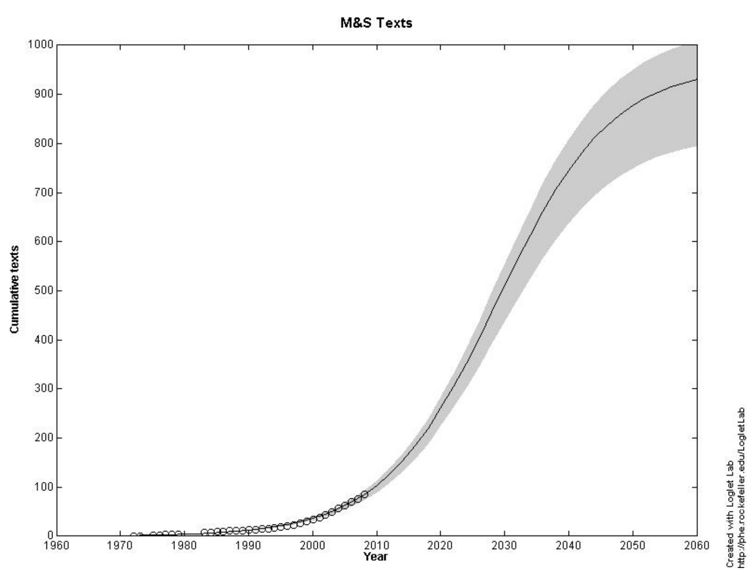

Figure 15. Logistic grwoth of M&S texts

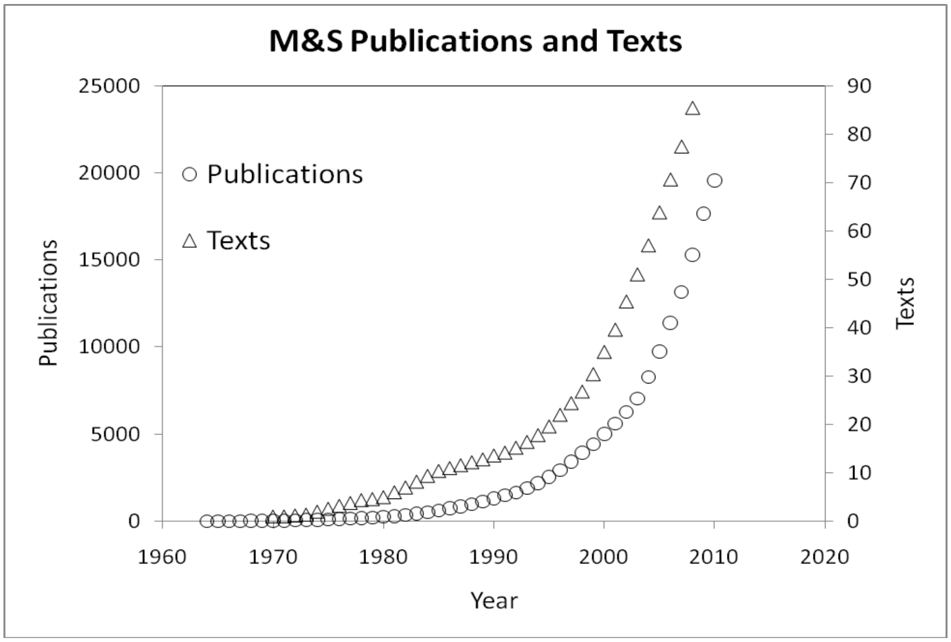

Figure 16. Early lead-lag relationship of M&S publications and texts

Summary of Research and Education Trajectories Correlation

Table 1 provides a summary of the results of correlating book publications to academic publications as one experimental means to predict education trajectories from research trajectories, as a means to suggest a method to project technology literacy needs.

Table 1. Technology Growth Midpoints and Periods

Technology	Year of Growth Midpoint	Period (10% to 90% of Growth)	Year of Growth Midpoint	Period (10% to 90% of Growth)
	Academic Publications		Book Publications	
FORTRAN	1988	31	1980	24
FEA	2015	38	1992	48
CFD	2015	28	2000	26
FDM	2020	44	2018	88
M&S	2025	30	2026	38

While FORTRAN studies provided an example most closely meeting intuited expectations, the other trajectories were of mixed results. The inconsistencies do not support the hypothesis that book (educational) trajectories can be correlated in consistent lead-lag relationships with academic publishing. Most likely, errors are attributable to the limited book publications records of the Library of Congress, and its use as a proxy for education text publishing. A more comprehensive study of academic text publications, their distribution, and especially the enrollment of students, would create results that are more valuable. The projection of M&S texts, an indicator of future knowledge and learning diffusion for this rapidly growing industry, is preliminary by the same accounts.

Research and Industry Standards Trajectories Correlation

A brief search of Internet sources provided approximate dates of first industry and professional organization validation and verification standards. Table 2 provides summary of the relationships between research publications trajectories and standards implementation.

Table 2. Year and Percent Growth at First Industry Standards

Technology	First Published Standards	
	Year	% Growth
FEA	~1995	~10
CFD	~1995	~8
FDM	N/A	N/A
M&S	~2012 (begun in 2010)	~10

Summary of Research and Industry Standards Trajectories Correlation

The timings of the implementation of industry first validation and verification standards is consistent across the similar but nonetheless diversely applied technologies. This provides initial support for projecting the timing of industry standards in other emerging similar technologies. This correlation might be useful in planning technological literacy initiatives, such as desired diffusion of information or skills in a technological area. Further research into the correlation of standards timing and commercial, educational, regulatory, or other critical or relevant diffusion might provide more information for planning technological literacy initiatives.

Future Directions

The ‘low hanging fruit’ method available for data collection in this unfunded study provided promising preliminary results. The logistic model for trajectories proved reliable and useful as the data set for academic publications was comprehensive and accessible. However, the data required to develop correlations with events and trajectories especially useful for indentifying and planning for technological literacy needs was much less comprehensive, detailed, or available.

To improve on the promising results of this study, the following are recommended:

- Seek catalogs or comprehensive databases of *collegiate text* books
- Gather commercial sales information from private entities and sources
- Complete a more thorough review of standards implementations
- Collect historic data from university annual course data: textbooks used; total enrollments; course offerings and times; etc.
- Consider the growth of similar changing applied technologies in other disciplines, such as biology, geology, meteorology, etc.
- QTF modeling of commercial M&S industry growth might better look at evidence of the diffusion of the popular underlying methodologies applied in M&S applications, such as agent-based modeling techniques, Bayesian statistics, fuzzy algorithms, and other probabilistic methods.

Conclusion

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. One such technique, logistic growth projection, provided good characterization of technological diffusion and adoption of several related computationally and numerically intensive analytical technologies. Results to correlate the growth of research in these technologies with commercial and educational events and trends provided mixed success, mainly because of the incompleteness of the commercial and educational data sets. Results do show that using QTF techniques to project technological change can be a useful tool to project technological literacy requirements and help guide planning for technological literacy initiatives.

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