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A review of selected recent advances in technological forecasting

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Abstract

During the past decade, there have been some significant developments in technological forecasting methodology. This paper describes developments in environmental scanning, models, scenarios, Delphi, extrapolation, probabilistic forecasts, technology measurement and some chaos-like behavior in technological data. Some of these developments are refinements of earlier methodology, such as using computerized data mining (DM) for environmental scanning, which extends the power of earlier methods. Other methodology developments, such as the use of cellular automata and object-oriented simulation, represent new approaches to basic forecasting methods. Probabilistic forecasts were developed only within the past decade, but now appear ready for practical use. Other developments include the wide use of some methods, such as the massive national Delphi studies carried out in Japan, Korea, Germany and India. Other new developments include empirical tests of various trend extrapolation methods, to assist the forecaster in selecting the appropriate trend model for a specific case. Each of these developments is discussed in detail.

Keywords: Technological forecasting; Environmental scanning; Delphi

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1. Environmental scanning

Forecasting by environmental scanning takes advantage of the fact that technological change often follows a standard sequence of steps. A typical sequence might be:

- Theoretical proposal
- Scientific findings
- Laboratory feasibility
- Operating prototype
- Commercial introduction

By observing a technological innovation at an early stage in this sequence, it may be possible to anticipate when it will reach later stages in the sequence, or at least provide warning that further developments may follow.

Using this method of forecasting means searching through the technical, trade and business literature to identify events that may foretell significant later developments. In the past, this has been a very labor-intensive process. The forecaster must formulate hypotheses based on initial findings, determine what subsequent items of information would be expected if the hypotheses are valid, then search for those items.

A major advance of the past few years has been using a computer for the "grunt work." Searching the literature can now be automated. Data mining (DM) and database tomography (DT) have become practical techniques for assisting the forecaster to identify early signs of technological change.

The use of computers for text searching does not eliminate the need for expert analysis. It does, however, multiply the effort of the experts by searching documents for words and phrases that have been determined to be important.

The task begins with a journal or publication database in computer-readable form. A sample of items from the database is taken and evaluated by expert analysts into two groups: relevant and not relevant to the subject matter. High-frequency single, double and triple word phrases are identified for the relevant and nonrelevant groups. The remainder of the database is then searched, using the high-frequency phrases from the relevant group as search terms and the high-frequency phrases from the nonrelevant group as NOT search terms. The result is a sorting of the entire database into relevant and nonrelevant items.

Table 1
Sources for life cycle data

R&D stage	Typical source
Basic research	Science Citation Index
Applied research	Engineering Index
Development	US Patents
Application	Newspaper Abstracts Daily
Social impacts	Business and Popular Press

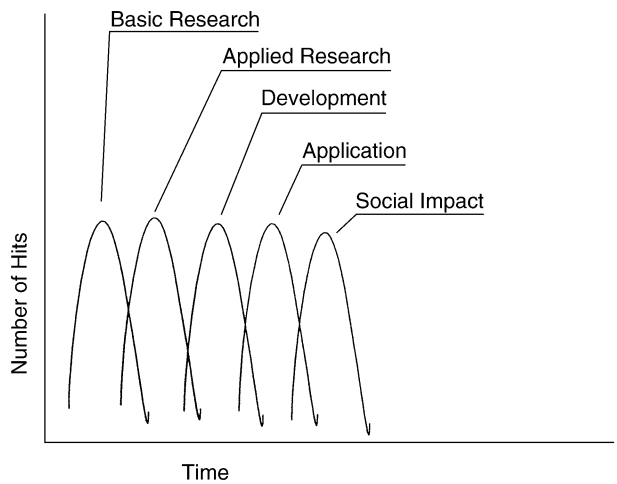

Fig. 1. Bibliometric estimate of stage of innovation.

In addition to simply identifying relevant documents, the search procedure can identify authors and institutions making significant contributions to the field of interest, journals carrying the most relevant articles and nation of origin of the contributions. This information can be used to identify likely sources of information about future developments.

Once a specific technological thrust has been identified, bibliometric methods can be used to determine its position in its life cycle. One possible approach uses a classification similar to that in Table 1 (adapted from Watts and Porter [1]).

A typical pattern might be that "hits" on relevant items in basic research would rise to a peak, then taper off as the "hits" on relevant applied research items began to increase. The approximate position of the technology in its life cycle could then be assigned with reasonable accuracy and leading indicators of later stages could be identified as soon as they appear. A qualitative illustration of this is shown in Fig. 1.

The use of computers to search large databases does not eliminate the need for expert analysis. It does, however, greatly ease the task of the forecaster by automating the search of the literature for things the forecaster has determined to be important.

2. Models

Causal models assume that the relevant variables and their linkages are known and can be described in mathematical equations (for example, eclipses of the sun and moon are forecast using causal models). Simultaneous solution of the equations, either in closed form or by computer simulation, then serves to forecast the future values of the variables.

Causal models have not been widely used by technological forecasters. Experience with them has not been satisfactory. The major problem is that, in many cases, even the relevant variables are not known, let alone the linkages between the variables. As a simple example, the effect of doubling the R&D budget on the rate of change of some technological parameter is impossible to predict with any degree of accuracy.

The use of causal models in technological forecasting is almost entirely limited to forecasting adoption or diffusion of innovations, where parameters such as rate of imitation by other adopters or rate of response to advertising can be measured. While these uses are important, they are very limited in scope.

Some of the recent developments in models for diffusion or adoption of innovations are the following:

- Bhargava [2] modified the Fisher-Pry model to have a time-dependent rate coefficient.
- Christodoulou et al. [3] used object-oriented programming to model competition between analog and digital cell phones.
- Dekimpe et al. [4] examined factors that made nations early or late adopters.
- Goldenberg and Efroni [5] used cellular automata to model discovery of needs by firms.
- Islam and Meade [6] empirically found that the imitation and innovation coefficients of a Bass model are not constant over several generations of a technology.

Developing good substitution models remains a fruitful area of research. The primary need is to identify the factors that affect the imitation and substitution coefficients of the existing models.

3. Scenarios

Scenarios are used to combine related but separate forecasts that bear on some topic of interest. Together, they provide an overall picture of the environment, as opposed to the small segments of the environment captured by each of the forecasts individually.

Scenarios have one or more of three general purposes:

- Display the interactions among several trends and events to provide a holistic picture of the future;
- Help check the internal consistency of the set of forecasts on which they are based;
- Depict the future in a way readily understandable by the nonspecialist in the subject area.

A significant recent development in generation of scenarios was by Jenkins [7], who used morphological analysis to eliminate incompatible combinations of factors, and goal programming to obtain compatible probability estimates for combinations of factors.

Gausemeier et al. [8] presented a five-step scheme for developing and utilizing scenarios. The key elements of their scheme are first, focusing on the decisions to be made and, second, taking into account the industry in which the forecaster is located, the industrial environment (including suppliers, customers, competitors and replacement products) and the global environment. Their scheme requires that the forecaster identify key factors, and projects at least three developments for every key factor. In addition, an ''influence matrix'' relating the influence of one factor on another must be prepared. Proprietary software is then used to generate a large number of scenarios. These are subjected to cluster analysis, to find ''bundles'' of similar scenarios. Finally, multidimensional scaling is used to prepare a ''map'' of the future. The final step is to identify the impacts of each possible cluster on the business. The intention of this scheme is to permit the business to prepare for an uncertain future by identifying the major uncertainties.

Because of their benefits, scenarios have become very popular as tools for business forecasting. However, scenario generation is still a highly subjective art. Tools such as cross impact can aid in scenario generation, but scenarios remain qualitative in nature.

4. Delphi

Delphi remains a popular technique for preparing forecasts. One of the most significant applications of Delphi within the past decade has been the preparation of massive national forecasts in Korea, Japan, Germany and India [9,10].

One significant methodological advance in use of Delphi was developed by Dransfeld et al. [11]. They used Bayesian weighting to combine responses to a Delphi questionnaire. They weighted the responses of the panel members on four different factors: experience in the industry, position in the company, position of the company in the industry, and self-rating on each question. For different questions, the ratings of the company in the industry would vary and self-ratings might vary. For each factor, the panel members were rated in one of five categories, designated A through E, in decreasing level of expertise.

The simplest case is when the panel members are asked to answer *yes* or *no* to a specific question. For a panel member in generic category *I*, the probability of saying *yes* about the future occurrence of event *F* when *F* will occur (correct forecast) is:

$$P_{\mathrm{I}}(Y/F) = p_{\mathrm{I}} \tag{1}$$

and the probability of saying *yes* about event *F* when *F* does not occur (incorrect forecast) is:

$$P_{\mathrm{I}}(Y/\overline{F}) = \overline{p}_{\mathrm{I}} \tag{2}$$

Assume there are n_{I} panel members in category I and of these y_{I} said *yes*. Then given the data (responses) from all panel members in all categories of expertise, for a given *yes* or *no* question, application of Bayes equation and binomial probability theory gives:

$$\frac{P(F/\mathrm{data})}{P(\overline{F}/\mathrm{data})} = \frac{\prod_{\mathrm{I=A}}^{\mathrm{E}} p_{\mathrm{I}}^{y_{\mathrm{I}}}(1-p_{\mathrm{I}})^{n_{\mathrm{i}}-y_{\mathrm{i}}}\pi}{\prod_{\mathrm{I=A}}^{\mathrm{E}} \overline{p}_{\mathrm{I}}^{y_{\mathrm{I}}}(1-\overline{p}_{\mathrm{I}})^{n_{\mathrm{i}}-y_{\mathrm{i}}}\pi} \tag{3}$$

where π is the a priori probability of correctly answering *yes* when *F* will occur.

On the assumption that the forecaster knows less about the subject than do the panel members, the forecaster can retain complete neutrality by assigning π the value .5. It then cancels out of Eq. (3). Since the panel members are experts in the subject matter (although with varying degrees of expertise), it is reasonable to assume that:

$$p_{\mathrm{I}} > .5 > \overline{p}_{\mathrm{I}},$$

that is, the probability of their correctly saying *yes* is greater than .5 and their probability of incorrectly saying *yes* is less than .5. However, the precise probabilities not only are not known, they cannot be known (i.e., the experts cannot be calibrated). Thus, Dransfeld et al. arbitrarily assigned values of p_{I} in the range .7 down to .6 in steps of .025 for the categories A through E, and values of $\bar{p}_{\mathrm{I}}$ from .325 to .425 in steps of .025 for the same categories.

The probabilities computed by this method involve some highly subjective inputs. Therefore, the results should not be quoted to more than one or two significant figures. It may be realistic to do no more than rank the resulting probabilities into categories such as *highly likely*, *quite likely*, *50−50*, *unlikely* and *very unlikely*. Nevertheless, this method gives a means for combining the estimates of panel members of varying expertise.

Delphi remains one of the most popular methods for technological forecasting. For large-scale national or industry forecasts, it is probably the only feasible method. Improvements in methodology for combining the panel members' estimates will enhance the utility of Delphi.

5. Extrapolation

Forecasting by extrapolation means that the forecaster assumes that the past of a time series contains all the information needed to forecast the future of that time series. An appropriate model is fitted to the historical data and the projection of that model becomes the forecast.

5.1. Selection of growth curves

Selecting the appropriate model for extrapolation is critical to forecasting success. If the wrong model is chosen, no amount of data accuracy or sophisticated fitting methods can save the forecast.

The two growth curves most commonly used by technological forecasters are the logistic or Pearl and the Gompertz. The formulas for the logistic is:

$$Y = \frac{L}{1 + ae^{-bt}} \tag{4}$$

The formula for the Gompertz is:

$$Y = Le^{-be^{-kt}} \tag{5}$$

The derivative of the logistic is:

$$\frac{bY(L-Y)}{L} \tag{6}$$

The derivative of the logistics is:

$$-bkY\ln\left(\frac{Y}{L}\right) \tag{7}$$

The rate of change of the logistic involves both level already achieved and distance to the upper limit, while the rate of change of the Gompertz involves only distance to the upper limit. These differences can have a significant impact on forecast accuracy. It is important, then, to choose the right growth curve to forecast a time series.

Fig. 2 shows both logistic and Gompertz curves on the same plot. They have been scaled so that both have value of 0.5 for $t=0$. Near the upper end, the two curves are very close together. However, this is not the region where a forecast is usually needed. Forecasts are usually needed near the toe of the curve. If the data really represent a logistic and a Gompertz is fitted, the forecast will be seriously in error. Likewise, if the data really represent a Gompertz and a logistic is fitted.

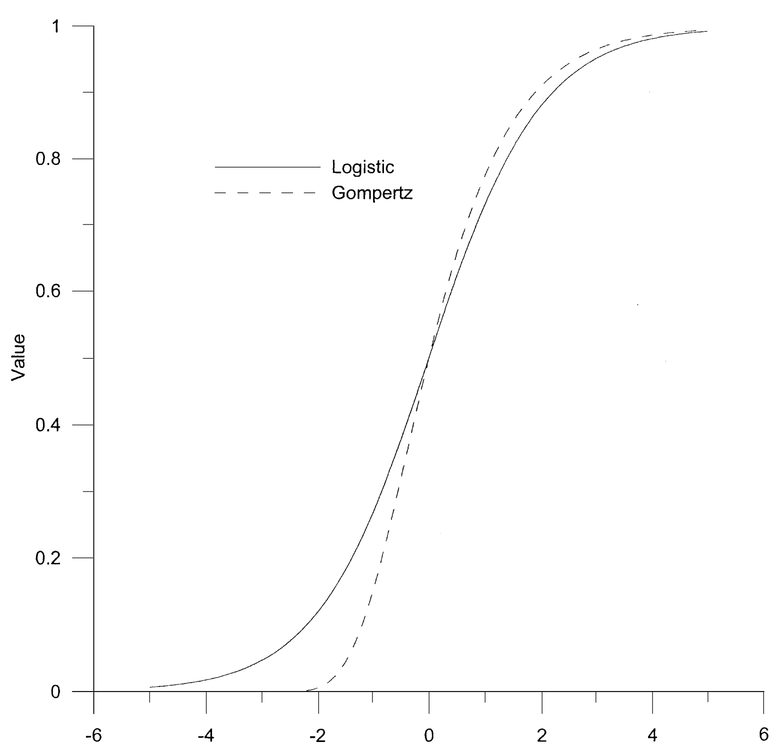

Fig. 2. Comparison of logistic and Gompertz curves.

Franses [12] has developed a method for choosing between the logistic and Gompertz curves. The method involves difference equations for the two formulas. The difference equation for the logistic is:

$$\log(\Delta\log \mathrm{Y_t}) \approx \mathrm{d_2} - \mathrm{ct} + (\log \mathrm{Y_t} - \log \mathrm{L}) \quad (8)$$

while that for the Gompertz is:

$$\log(\Delta\log Y_t) = d_1 - kt \quad (9)$$

where d_1 and d_2 are nonlinear functions of the location and shape parameters of the curves, and Δ is the difference operator, $\Delta z = z_t - z_{t-1}$.

Fig. 3 shows these two equations for the curves of Fig. 2. The expression for the Gompertz curve is linear in t, while the expression for the logistic curve is nonlinear in t. Thus, a test for distinguishing between the two growth curves is the following auxiliary regression:

$$\log(\Delta\log Y_t) = \delta + \gamma t + \tau t^2 \quad (10)$$

If τ is significantly different from zero, then the forecaster can conclude that the logistic is a better model for the data than is the Gompertz.

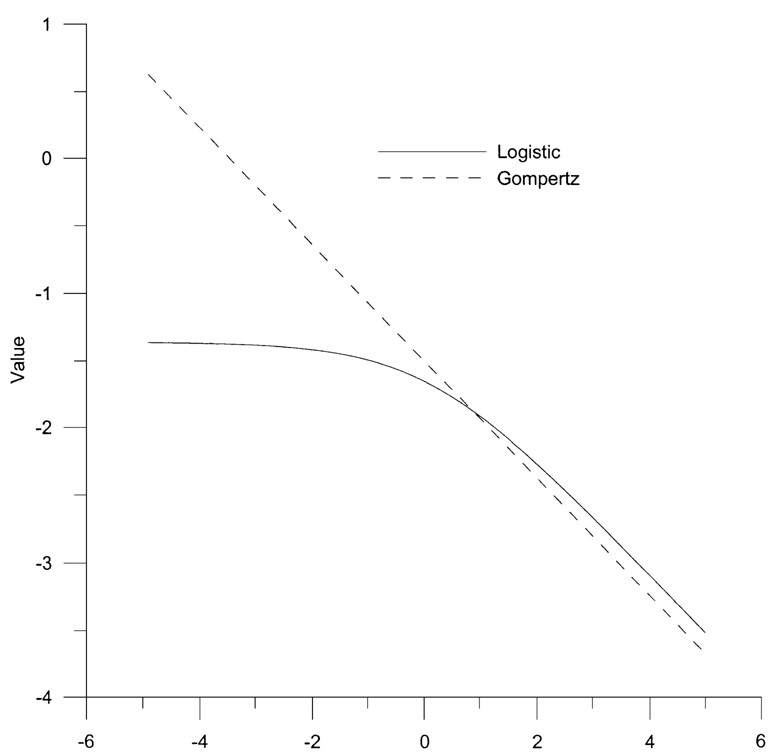

Fig. 3. Log delta log.

Table 2
Significance of auxiliary regression

Coefficient	δ	γ	τ
Value	− 1.69295706	− 0.21385756	− 0.032659334
S.D.	0.0044360154	0.0010252906	0.00039687511

To illustrate the use of the auxiliary regression, Eq. (10) is fitted to the data for the logistic curve shown in Fig. 2. The coefficients and their standard deviations are shown in Table 2. As can be seen from Table 2, the coefficient τ of t^2 is highly significant, confirming that the data do in fact come from a logistic rather than a Gompertz process.

One of the advantages of this method of selecting the proper growth curve is that all the data are used in the auxiliary regression. It is not necessary to hold out some data to determine how well the fitted curve fits the held-out data.

5.2. Three-parameter logistic fitting

It is generally recommended that the forecaster not try to estimate the upper limit of a growth curve by using a fitting procedure to derive L as well as a and b. This is especially true if only data from the toe of the curve are available. The influence of the upper limit is not strongly felt at that level and the estimate of L will involve a great deal of uncertainty.

DeBecker and Modis [13] generated a large number of logistic curves by computer simulation, intentionally introducing random errors in the computed values, then extracting all three parameters by a fitting procedure. Using the true values for the logistic, they computed confidence bounds on the parameters.

The analysis runs as follows. Let:

$$y(t) = \frac{L}{1 + e^{-a(t-t_0)}} \tag{11}$$

This is the conventional logistic, with the coefficient of e replaced by e^{t_0}, where t_0 is the time at which $y = 0$. Now, if we consider $y(t_i)$ to be one observation from the random variable $Y(t_i)$, we can form the expression:

$$U = \sum_{i=1}^{n} \left(\frac{y(t_i) - E(Y(t_i))}{\sigma(Y(t_i))} \right)^2 \tag{12}$$

where E is the expected value and σ the standard deviation.These are, respectively,

$$E(Y(t_i)) = \frac{L}{1 + e^{-a(t-t_0)}} \tag{13}$$

and

$$\sigma^2(Y(t_i)) = \frac{L}{(1 + e^{-a(t-t_0)})(1 + e^{a(t-t_0)})} \tag{14}$$

U is approximately χ^2 with $n-3$ degrees of freedom.Parameters L, a and t_0 are selected to minimize U. These are then the fitted values for the three parameters.

The uncertainties on the fitted value of L are given in Table 3, for selected errors in $y(t)$ and selected confidence levels.

For instance, if the estimated error in each data point is 1% of its measured value and the value of the largest data point is 20% of the fitted upper limit, then with 90% confidence the true upper limit is within 11% of the fitted value of L. Note that for even modest errors in the data (i.e., 10%) the confidence bounds on L become quite large. This simply confirms the admonition that attempting to extract the upper limit from data early in the growth of a logistic is not a very good idea.

The article gives tables for several different maximum values of $y(t)$ as a fraction of fitted L. Note that the calculations in the article are based on 20 data points for each case. If the forecaster has fewer than 20 data points available, the table values are probably an underestimate of the true confidence bounds.

5.3. Robustness of growth curve models

Young [14] conducted a "competition" among nine different growth curve models, using a collection of some 46 data sets representative of those encountered by technological forecasters. In each data set, the last three data points were held out to be compared with the forecasts based on the earlier data points.

Two important findings come out of the research.

First, the models giving best fit to the historical data, as measured by mean square error, were in general not the best forecasting models. This reinforces the idea that a good forecasting model is one that will fit the future data, not necessarily the one that best fits the past data. In short, getting the model that matches the process that generated the data is more important than getting a good fit to the historical data.

Second, if the upper limit is not known, neither the logistic nor the Gompertz, nor any of their variants such as Mansfield-Blackman, performs very well. This reinforces the idea that

Table 3
Uncertainty in L for selected error levels and maximum data value 20% of estimated L

Confidence bounds	Percent error in data values					
	1	5	10	15	20	25
70	4.9	22	51	120	190	290
75	5.9	27	60	150	230	360
80	6.8	32	73	180	280	430
85	8.6	37	92	250	360	480
90	11	48	120	300	440	730
95	15	65	160	480	640	
99	65					

attempting to extract the upper limit from data representing the early portion of the growth curve is not a good idea.

6. Probabilistic forecasts

The methods of forecasting discussed above all give a single number as the forecast. Probabilistic forecasts, by contrast, give a range of outcomes and the probability distribution across that range. Typically, the range of outcomes and distribution of the outcomes are determined by computer simulation.

6.1. Stochastic cellular automata model of diffusion

A cellular automata model can be depicted as a two-dimensional array of cells. Some cells are "alive," while others are "dead" at the outset. There are rules prescribing how cells transition from one state to the other, depending upon the states of their neighbors. In typical applications of cellular automata, the rules describing transitions are deterministic. However, the rules can also be probabilistic.

Bhargava et al. [15] describe a stochastic cellular automata model in which some cells start as "adopters" and the remainder as "potential adopters." Each potential adopter cell becomes an adopter according to a probabilistic computation. If the potential adopter cell is adjacent to an adopter cell, they draw a random number. If the number exceeds a threshold value x, the cell becomes an adopter. Thus, the probability of adopting if an adjacent cell has already adopted is $1-x$. In their simulation, x is steadily decreased as market saturation is reached.

Fig. 4 shows some of their results. The jagged line is a single simulation run. The smooth line is the average of 50 simulation runs.

The primary focus of their research was to determine the influence of the number of initial adopters. As might be expected, market saturation is achieved more quickly as the number of initial adopters is increased. However, this process quickly reaches a limit, beyond which increasing the number of initial adopters has little effect on the rate of growth of the adopter population.

Note that in their model, the only influence operating is imitation. The model could be modified to include innovation as well, by assigning to each potential adopter cell a probability of adopting spontaneously, even if it is not adjacent to an adopter cell.

6.2. Choice among multiple generations of a product

In many cases, there are several generations of a product available on the market at the same time. Adopters may choose an older generation because of considerations such as cost, availability of workers familiar with the product, compatibility with existing equipment, etc. Conversely, adopters may choose a more recent generation because of factors such as higher productivity or greater cost-effectiveness.

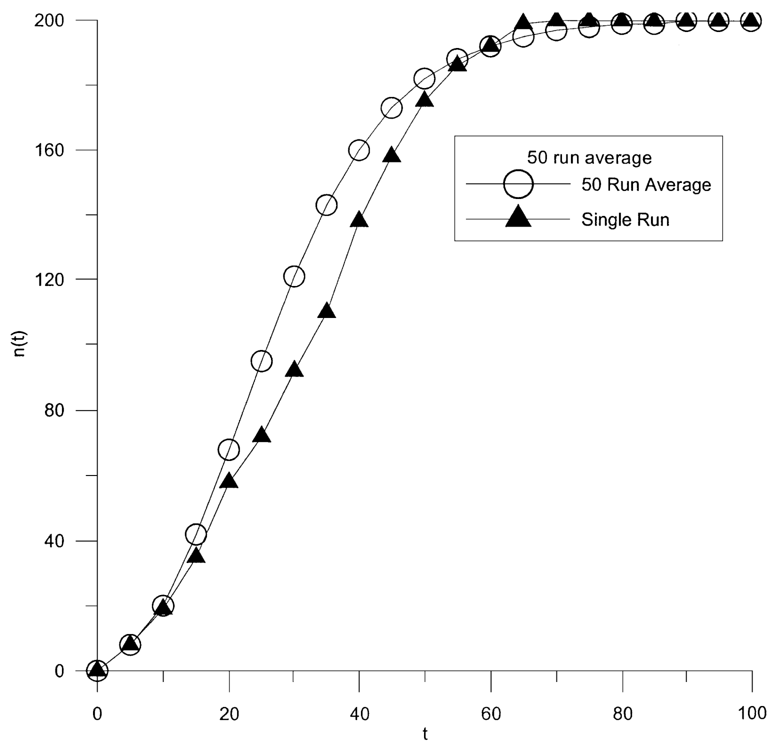

Fig. 4. Plot of number of adopters vs. time for stochastic cellular automata (from Bhargava et al.).

Jun and Park [16] present a model in which the probability of an individual purchasing generation k at time t, provided he has not bought an earlier generation, is given by the multinomial logit probability:

$$P_t^{(0;k)} = \frac{\exp(V_t^{(0;k)})}{\exp(c) + \exp(V_t^{(0;1)}) + \exp(V_t^{(0;2)}) + \ldots + \exp(V_t^{(0;n_t)})}$$

$$k = 1, 2, \ldots, n_t \qquad (15)$$

Where $V_t^{(o;j)}$ is the value to the purchaser of generation j at time t, based on factors such as price, design, advertising, etc.

A similar equation gives the probability of upgrading to generation j when the purchaser already owns generation i.

Jun and Park fit their model to data from IBM mainframe sales over several generations and DRAM shipments over several generations. Their model shows a lower SSE for the fitted region, but does not seem to forecast as well as the Bass model. This gain emphasizes the point that the forecaster wants a method that will fit *future* data well, rather than one that fits *past* data well.

7. Technology measurement

For many technologies, it may be sufficient to forecast a single parameter. However, a single parameter is insufficient for technologies that have multiple parameters that can be traded for one another. In addition, the forecaster may need a technology measure that exist at a higher level of aggregation than that of individual devices.

Kayal [17] presented a technology measurement technique suited for aggregated level measures, technology cycle time. This is the median age of the patients cited in a patent application. The shorter this time, the more rapid the pace of technological progress.

Table 4, taken from Kayal, shows technology cycle time for high and low temperature superconductors.

This approach may be suitable for determining relative rates of advance for different fields, for determining rate of progress in one country as compared with another, or for identifying sources of contributions to rapid progress.

Ayres [18] has proposed a measure of the aggregate technology available or utilized in an industry sector or nation. It involves two efficiency factors; the efficiency of conversion of energy (that part of the energy flux that is available to do useful work) and the efficiency of service delivery (ratio of final work output to energy input). The product of these two represents the efficiency of conversion of raw materials to final useful goods and services. Ayres demonstrates, through use of historical data for the United State, that these two efficiency ratios can be calculated, and an overall measure of the US economy's efficiency of conversion of natural material into useful goods and services can be obtained. For 1991, the calculated overall conversion efficiency was about 0.04, obviously leaving much room for improvement. This technology measurement approach allows the forecaster to compare different industry segments or different nations and to forecast overall efficiencies for the future.

8. Chaos theory

It would be strange if chaos theory had not influenced technological forecasting. In fact, it has. One specific example is that of Modis and DeBecker [19], who showed that, at the juncture of two successive Logistic curves, chaotic behavior can sometimes be found. They

Table 4
Technology cycle time for high and low temperature superconductors

Year	High T_c	Low T_c
1988	1.8	6.6
1989	10.2	6.9
1990	7.0	7.0
1991	6.2	6.9
1992	4.3	7.9
1993	3.4	7.3
1994	3.9	5.0

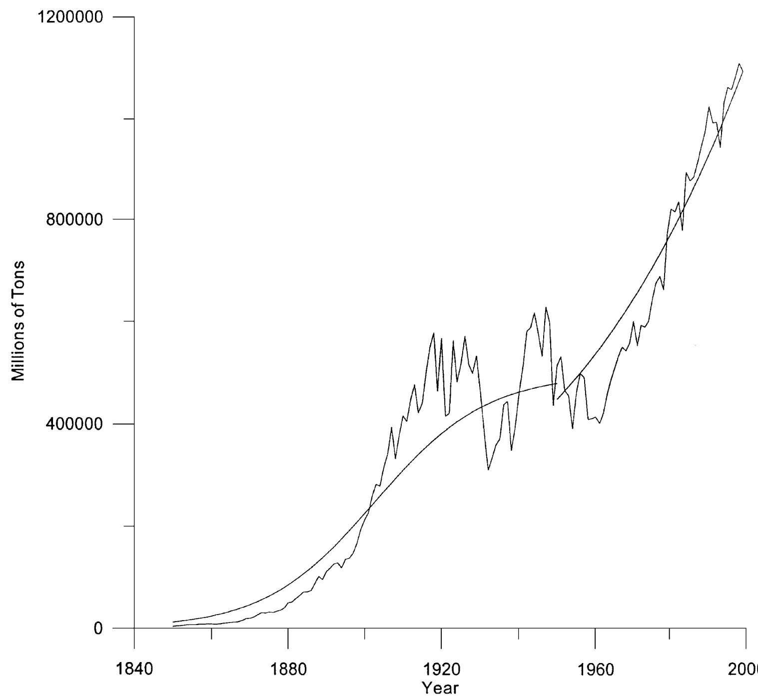

Fig. 5. Bituminous coal production with successive curves fitted.

point out that the behavior is not true chaos, but does involve oscillations about some final value. They provide several examples. One of these is shown in Fig. 5. This plot shows production of bituminous coal in the United States from 1850 to 1999. The plot appears to be two growth curves, the second one following a "plateau" centered about 1950. A logistic curve is shown fitted to the first part of the historical data. Since no upper limit is known for the second part of the growth, an exponential curve was fitted. The key issue is the oscillation about the fitted curves in the region where one "tops out" and the other begins.

9. Summary

Within the past 10 years, there has been significant progress in technological forecasting methodology. Some of this progress represents improvements in existing techniques, such as extrapolation and environmental scanning. However, the innovations in stochastic methods represent tools previously unavailable to the technological forecaster.

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