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Review of Methods for Forecasting the Market Penetration of New Technologies

S. T. Gilshannon
D. R. Brown

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Prepared for the U.S. Department of Energy
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Richland, Washington 99352

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Summary

In 1993 the U.S. Department of Energy's (DOE) Office of Energy Efficiency and Renewable Energy (EE) initiated a program called Quality Metrics. In short, Quality Metrics was developed to measure the costs and benefits of technologies being developed by EE research and development (R&D) programs. The impact of any new technology is, of course, directly related to its adoption by the market. Therefore, the techniques employed to project market adoption are critical to measuring a new technology's impact. The purpose of this study, conducted by the Pacific Northwest National Laboratory for DOE's Office of Energy Management (OEM), was to review current market penetration theories and models and develop a recommended approach for evaluating the market penetration of OEM's technologies.

The following commonly cited innovation diffusion theories were reviewed to identify analytical approaches relevant to new energy technologies:

- the normal noncumulative adopter distribution method
- the Bass Model
- the Mansfield-Blackman Model
- the Fisher-Pry Model
- a meta-analysis of innovation diffusion studies.

Of the four theories reviewed, the Bass and Mansfield-Blackman models were found to be the most applicable to forecasting the market penetration of electricity supply technologies. Their algorithms require input estimates which characterize the technology adoption behavior of the electricity supply industry. However, inadequate work has been done to quantify the technology adoption characteristics of this industry. Therefore, until more data becomes available to support the parameter estimates which govern these market penetration algorithms, the use of an innovation diffusion theory for forecasting the electricity supply industry's adoption of new technologies will be difficult to defend.

The following energy technology market penetration models were also reviewed to identify analytical approaches most relevant to OEM-funded technologies:

- DOE's Renewable Energy Penetration (REP) Model
- DOE's Electricity Capacity Planning Submodule of the National Energy Modeling System (NEMS)
- the Assessment of Energy Technologies (ASSET) model by Regional Economic Research, Inc.

- the Market TREK model by the Electric Power Research Institute (EPRI).

The two DOE models were developed for electricity generation technologies whereas the Regional Economic Research and EPRI models were designed for demand-side energy technology markets. Therefore, the review and evaluation focused on the DOE models. The general structures of NEMS and the REP Model are similar and applicable to forecasting the market penetration of OEM-funded technologies. Both models allocate market shares via a logit function driven by the cost of the competing technologies. Both models have mechanisms for adjusting technology costs from year to year, but the mechanisms differ. The REP model applies an initial risk premium to new technologies that declines over time via a Bass model algorithm.[a] In contrast, NEMS applies the combination of a technology optimism factor and a learning factor to adjust technology costs. While the two adjustment mechanisms may seem quite similar, there is a significant difference. The REP model adjustment is driven only by the passing of time, while the NEMS adjustment is a function of the cumulative market penetration. The NEMS adjustment is credible because it is driven by actual market factors. On the other hand, NEMS does not allow for technology improvements driven by any other factor, such as R&D.

The recommended market penetration model framework, which combines features drawn from NEMS and the REP model, is outlined below. This is a generic framework which will have to be tailored to fit the many technologies of interest to OEM, but the basic features should be common for all technology applications.

Market Penetration Model Framework

I. Determine Starting Positions

   A. Initial Catalog of Cost and Performance Characteristics for Each of the Competing Technologies (current and mature characteristics for immature technologies)
   B. Initial Inventory (Stock) of Each of the Competing Technologies
   C. Initial Year Available (for immature technologies)
   D. Market Demand Projections for Each Year Throughout the Forecast Horizon

II. Determine Cost Adjustments

   A. Immature Technology Risk Premium (function of units installed)
   B. R&D "Learning" (function of time)
   C. Utilization "Learning" (function of units installed)
   D. Production Economies-of-Scale (function of units installed)

III. Calculate the Life-Cycle Cost (LCC) of Each Technology

(a) The REP model uses the Bass algorithm to adjust a technology's cost from one year to the next, and not to directly estimate market share, which is how the Bass model is generally applied.

IV. Calculate Annual Market Shares

A. Eliminate Non-Competitive Options (LCC too high relative to lowest LCC)
B. Calculate Initial Market Shares (fractions) with Logit Function
C. Calculate Initial Market Shares (capacity)
D. Adjust Market Shares for Technology Capacity Constraints (e.g., production limits, resource limits, environmental limits)

V. Determine Annual Re-Adjustments Resulting from New Market Shares

A. Inventory of Each Technology
B. Technology Cost and Performance
C. Life-Cycle Cost

Abbreviations

ASSET	Assessment of Energy Technologies
DOE	U.S. Department of Energy
DSM	demand-side management
EAR	economic attractiveness ratio
ECP	electricity capacity planning
EE	Office of Energy Efficiency and Renewable Energy
EPRI	Electric Power Research Institute
FAR	financial attractiveness relationship
LCC	life-cycle cost
LCOE	levelized cost of energy
LF	learning factor
LP	linear program
MLE	maximum likelihood estimation
NEMS	National Energy Modeling System
OEM	Office of Energy Management
OLS	ordinary least-squares
PB	payback
R&D	research and development
RE	renewable energy
REP	Renewable Energy Penetration

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1.0 Introduction

In 1993 the U.S. Department of Energy's (DOE) Office of Energy Efficiency and Renewable Energy (EE) initiated a program called Quality Metrics. In short, Quality Metrics was developed to measure the costs and benefits of technologies being developed by EE research and development (R&D) programs. The impact of any new technology is, of course, directly related to its adoption by the market. Therefore, the techniques employed to project market adoption are critical to measuring a new technology's impact. The purpose of this study, conducted by the Pacific Northwest National Laboratory[a] for DOE's Office of Energy Management (OEM), was to review current market penetration theories and models and develop a recommended approach for evaluating the market penetration of OEM's technologies.

"Innovation Diffusion" is the term used by most of the literature addressing the issue of the market's adoption of a new technology over time. The "diffusion" effect is defined as the cumulatively increasing degree of influence on an individual to adopt or reject an innovation. Innovation diffusion theory has been developing since the early 1960's and several core approaches have survived scrutiny to be commonly applied today. This report summarizes the general arguments underlying each of the most well-established diffusion theories, and how each is applied to the market penetration modeling process.

Innovation diffusion theory was developed to recognize that the cost of competing products is not the sole determinant of consumer behavior. The theory attempts to account for the pattern that few people (or firms) will adopt a technology about which little is known. As more is learned about the technology, acceptance for it grows. For example, although technology X has just achieved a lower life-cycle cost than technology Y, technology X will not displace 100% of technology Y's market right away. Instead, technology X's share of the market will grow at a rate over time that resembles an s-shaped curve. Most of the innovation diffusion models are based on the use of a logistical (or "logit") function to explain this pattern. A logit function is simply an exponential function that creates an s-shaped curve representing a market share growth process.

This report explains the key concepts, algorithms, advantages, and disadvantages of the following widely recognized and used innovation diffusion theories:

- the normal noncumulative adopter distribution method (Rogers 1967, which was revised in 1983)
- The Bass Model (1969)
- the Mansfield-Blackman Model (1971)

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- the Fisher-Pry Model (1971)
- a meta-analysis of innovation diffusion studies (1990).

The report also summarizes several current applications of innovation diffusion theory and market-sharing algorithms in forecasting the adoption of new energy technologies. These include

- the Renewable Energy Penetration (REP) Model (1993)
- the Electricity Capacity Planning (ECP) Submodule of the U.S. Department of Energy's National Energy Modeling System (NEMS) (1995)
- the Assessment of Energy Technologies (ASSET) software developed by Regional Economic Research, Inc. (1994)
- the Market TREK software developed by the Electric Power Research Institute (EPRI) (1994).

Finally, the report presents some recommendations for applying the innovation diffusion principles and market-sharing algorithms outlined herein.

2.0 Innovation Diffusion Theories

This section contains a summary of several innovation diffusion theories. They are presented in chronological order with respect to the year in which each theory was first published. Each summary presents the theory's key concepts; the method used to derive an s-curve, including methods for deriving particular coefficients; required inputs; advantages and disadvantages; and best references for further inquiry.

2.1 The Normal Noncumulative Adopter Distribution

A number of marketing academicians have based their diffusion theories on the notion that the noncumulative proportion of an innovation's adoption over time follows a normal distribution. Everett M. Rogers first proposed this theory in 1967. In 1983, he expanded this theory by including a simple method of using a standardized set of adopter categories in determining the shape of the noncumulative adopter distribution curve and, hence, the rate of a new technology's adoption.

2.1.1 Key Concepts

The assumption that the noncumulative adoption follows a normal distribution allows the analyst to simply use the mean time of adoption (t*), and the standard deviation (σ) to construct five adopter categories (see Table 2.1 and Figure 2.1). Developing adopter categories is useful in predicting the continued acceptance of an innovation. This has become the most widely accepted method for categorizing adopters.

Table 2.1. Normal Noncumulative Adopter Distribution Categories

Adopter Category	% Adopters	Area Covered Under Normal Curve
Innovators	2.5	Beyond $t - 2\sigma$
Early Adopters	13.5	Between $t - \sigma$ and $t - 2\sigma$
Early Majority	34.0	Between t and $t - \sigma$
Late Majority	34.0	Between t and $t + \sigma$
Laggards	16.0	Beyond $t + \sigma$

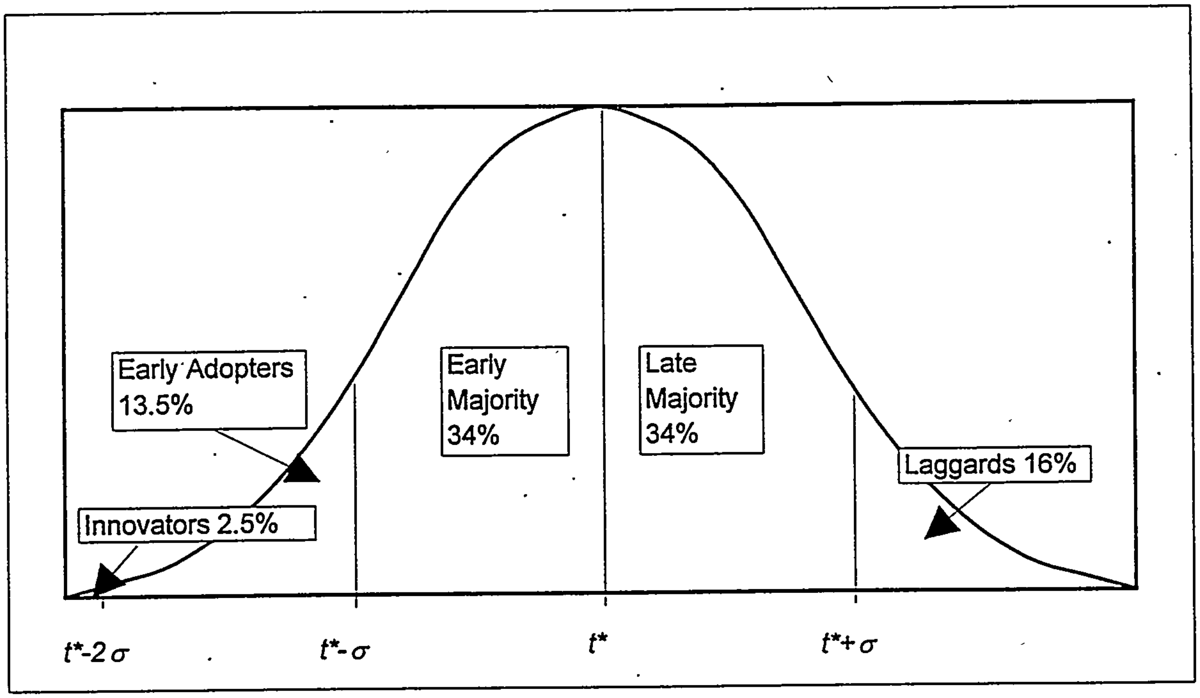

Figure 2.1. Normal Noncumulative Adopter Distribution and Categories

2.1.2 The S-Curve

Since the percentage of adopters in each category is standard, the analyst needs only to know the mean time of adoption (t*) and its standard deviation (σ) to derive the shape of the noncumulative adopter distribution. The analyst can then translate the noncumulative adopter distribution into a cumulative "s-curve" adoption pattern as a function of time. The t* point becomes the inflection point of the s-curve and the shape is determined by the standard deviation.

2.1.3 Required Inputs

- Estimate the mean time of adoption (t*) (i.e., the point at which adoption reaches its maximum rate; also known as the inflection point on the s-curve).

- Estimate the standard deviation of the mean time of adoption (σ).

These estimates must be derived by expert judgment unless a statistically valid sample of sales data exists.

2.1.4 Advantages and Disadvantages

The categorization scheme based on a normal distribution is perhaps the easiest to use of all the innovation diffusion methods, but perhaps the most inaccurate and theoretically flawed. Its popularity is borne of its ease of use and not of its accuracy as a forecasting tool.

The assumption that the noncumulative adoption of all new technologies follows a normal distribution is false. Many, if not most, of the noncumulative adoption distributions are skewed to one side of the mean or the other. No one has provided empirical or analytical justification to show that the size of the adopter categories should be the same for all new technologies.

This approach also assumes that the new technology will eventually displace the market share of all of the competing technologies. A new technology, however, may not garner all of the market over time. Therefore, this is not a valid approach for forecasting the market penetration of most energy technologies.

2.1.5 Best References

Mahajan, V., E. Muller, and R. Srivastava. 1990. "Determination of Adopter Categories by Using Innovation Diffusion Models." *Journal of Marketing Research* 27:37-50.

Peterson, R. A. 1973. "A Note on Optimal Adopter Category Determination." *Journal of Marketing Research* 10:325-329.

Rogers, E. M. 1967. "Mass Communication and the Diffusion of Innovations: Conceptual Convergence of Two Research Traditions." Paper presented at the Association for Education in Journalism, Boulder, Colorado.

Rogers, E. M. 1983. *Diffusion of Innovations*. 3rd ed. Free Press, New York.

2.2 The Bass Model

Frank Bass developed a logit function in 1969 which recognizes that new technology adoption patterns are not so easily generalized as the assumptions borne of the normal noncumulative adopter distribution theory. The Bass logit function allows the analyst to construct a market penetration s-curve which is not necessarily derived from a normal noncumulative adopter distribution.

2.2.1 Key Concepts

This model has a number of analytic properties that aid in determining the number and size of adopter categories and the shape of the s-curve over a given time horizon. A coefficient of "innovation" and another for "imitation" are the key ingredients of this logit function. The values of these coefficients vary with industry and type of innovation. The usefulness of this model depends on the quality of the information determining the value of these two coefficients.

2.2.2 The S-Curve

Three values are essential for using the Bass Model's key set of equations (Equations 2.1 through 2.3). First, p represents the coefficient of innovation (also known as the coefficient of external influence). In the Bass Model "innovators" are present at any stage in the diffusion process, so this value should refer to those who are not influenced in the timing of their adoption by the number of those who already have adopted the technology. Second, q represents the coefficient of imitation (also known as the coefficient of internal influence). This represents those who were influenced by the number of previous adopters. Figures 2.2 and 2.3 illustrate how innovators and imitators are mapped on a noncumulative adopter distribution. Third, m is the size (or total population) of the market. Another set of values is also necessary when the analyst has little or no data and cannot easily estimate p and q values. An algebraic estimation procedure as well as a general guide to picking appropriate p and q values can be found in Section 2.2.4.

- Cumulative Fraction of Adopters (S-Curve)

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + (q/p)e^{-(p+q)t}} \tag{2.1}$$

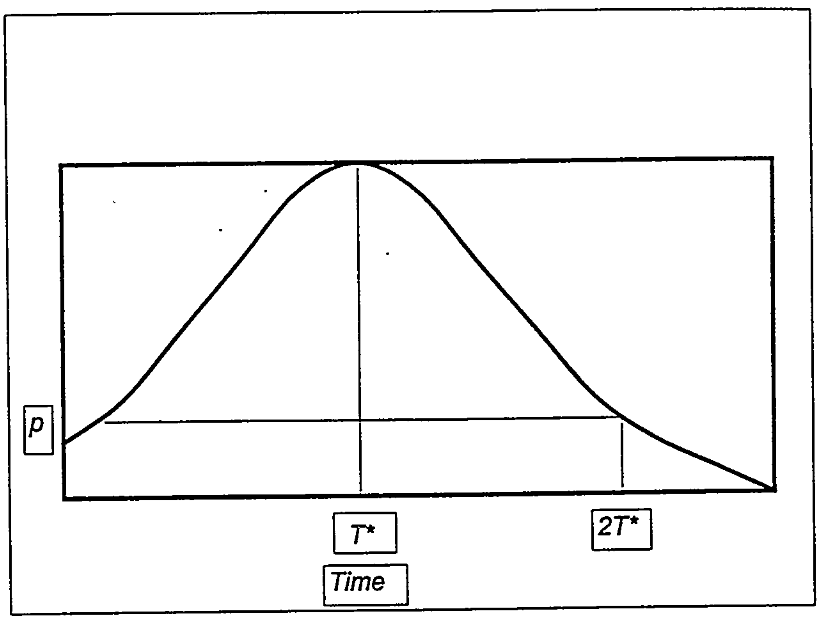

Figure 2.2. Noncumulative Adopter Distribution Under Bass Model

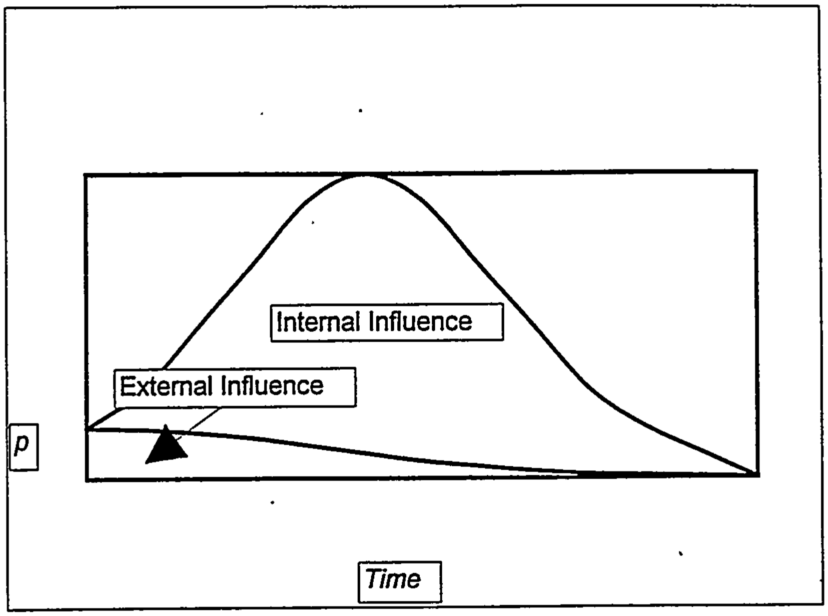

Figure 2.3. Adoption Distribution by External and Internal Influences

- Noncumulative Distribution (rate of diffusion at time t)

$$f(t) = \frac{p(p + q)^2 e^{-(p+q)t}}{(p + qe^{-(p+q)t})^2} \tag{2.2}$$

- Peak Adoption Rate (t*)

$$t* = -(1/(p + q)) * \ln (p/q) \tag{2.3}$$

2.2.3 Number and Size of Adopter Categories

The points of inflection in the noncumulative distribution curve serve as a way to identify the size of adopter categories and the duration of the adoption process. Being able to estimate t* when there are limited data for estimating p and q may not be good enough because the adoption patterns of different technologies and markets vary with respect to time. An estimate of the relative rate at which an innovation will be adopted is important in determining the width of the noncumulative adopter distribution. The analyst can set the width of the noncumulative distribution by estimating several trends in the technology's likely adoption rate over time. In general, as q/p increases, the percentage of adopters in the groups at either tail of the distribution also increases while the two groups on either side of the mean (t*) shrink in of the mean (t^*) shrink in size. Or, when not considering adoption categories, higher values for p increase the amount of adoption in early years, while higher values for q increase adoption in later years.

Equations 2.4 and 2.5 help define the shape of the noncumulative distribution and explain some analytic properties of the Bass Model. Figure 2.4 illustrates these properties. Values for T_1 and T_2 may be useful for checking estimates of the p and q values derived from the estimation procedure described in Section 2.2.4. For example, with the values $p = 0.0025$ and $q = 0.3$ plugged into Equations 2.4 and 2.5, T_1 will equal almost 12 years while T_2 will equal approximately 27 years. Perhaps this result does not coincide with the estimates of experts on the technology and the market. If it is easier to estimate the relative shape of the s-curve over a given amount of time than it is to estimate p and q values, then this type of gaging technique may help derive more trustworthy p and q values. Figure 2.5 shows examples of how various combinations of p and q values affect the shape of the market penetration curve.

$$T_1 = -(1/(p + q)) * \ln[(2 + \sqrt{3}) * (p/q)] \tag{2.4}$$

$$T_2 = -(1/(p + q)) * \ln[(1/(2 + \sqrt{3}) * (p/q)] \tag{2.5}$$

2.2.4 p and q Estimation

As Vijay Mahajan and Subhash Sharma (1986) explain, estimating the values of p and q requires knowledge of t^*, the point when the maximum rate of adoption occurs and two of the following three variables: (n^*), the noncumulative number of adopters at point t^*; (N^*), the cumulative number of adopters at t^*; and (m), the population of adopters. Determining these values requires either actual data, using an analogous product as a proxy, or expert judgment. Equation 2.6 can be used to solve for m, n^*, or N^* if two of these three variables are known, in addition to knowing t^*. Then p and q can be calculated via Equations 2.7 and 2.8.

$$t^* = [(m - N^*)/2n^*]\left[\ln\left(\frac{m}{(m-2N^*)}\right)\right] \tag{2.6}$$

$$p = \frac{n^*(m - 2N^*)}{(m - N^*)^2} \tag{2.7}$$

$$q = (n^*m) / (m - N^*)^2 \tag{2.8}$$

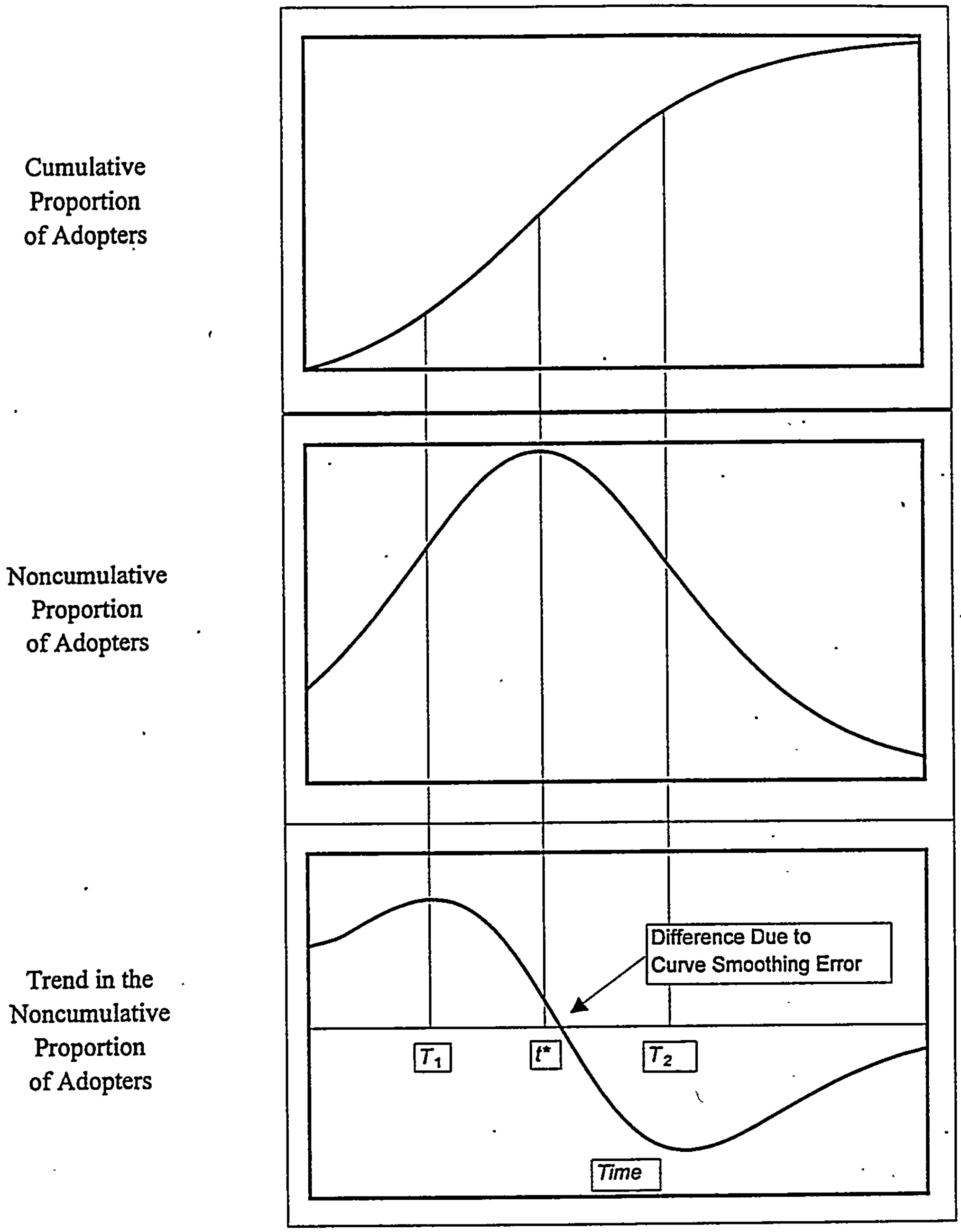

Figure 2.4. Analytic Properties of the Bass Model

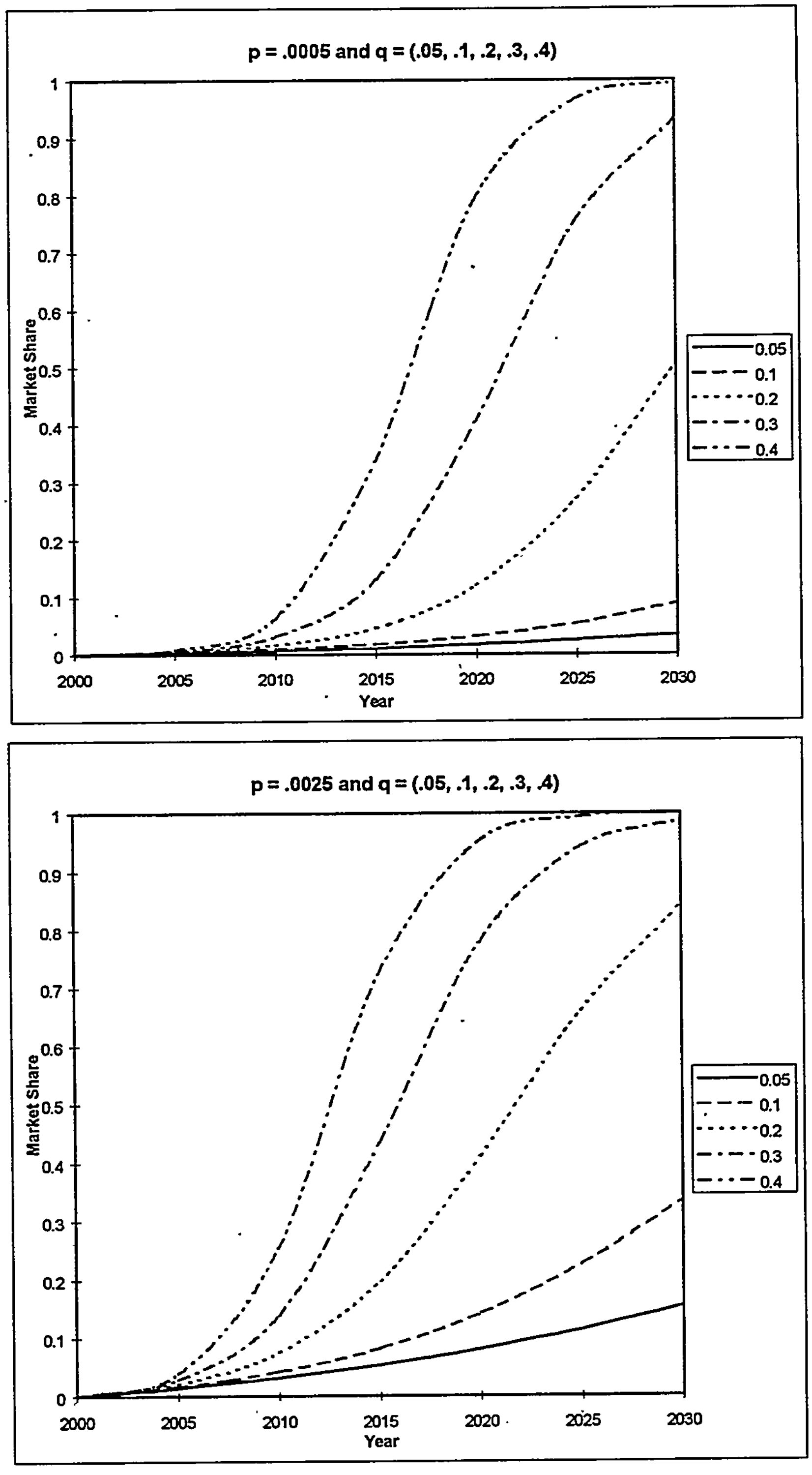

Figure 2.5a. Examples of Market Penetration Curves Under Bass Model

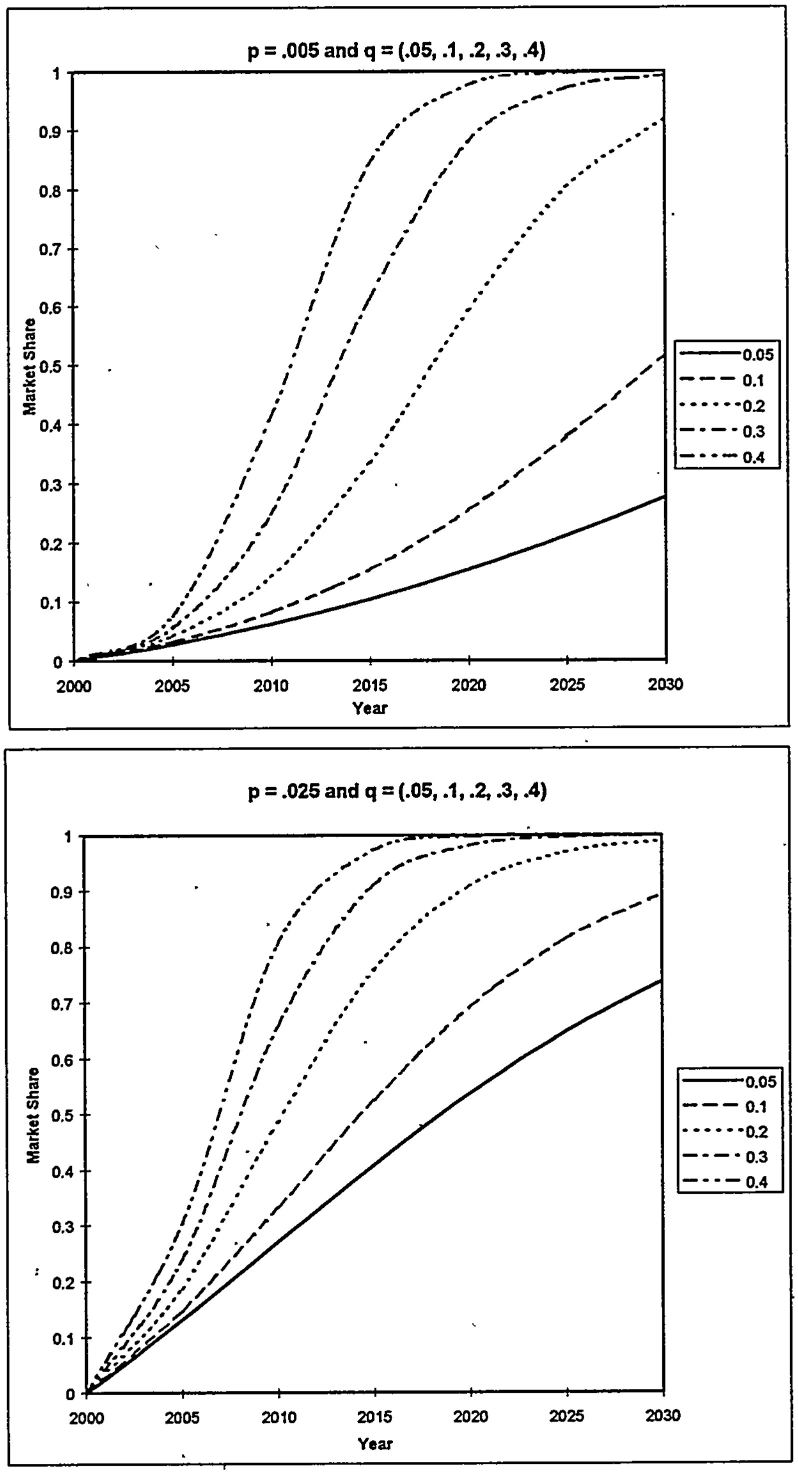

Figure 2.5b. Examples of Market Penetration Curves Under Bass Model

Of course, knowing the values for t^*, N^*, n^*, and m (or at least three of these four variables) would be an extremely lucky and rare case. Not knowing these values, however, does not make this model useless. A defensible estimate of t^* and m, as well as a general expectation of whether the new technology will be most heavily adopted in the earlier or later years is all that is necessary for finding reasonable p and q values. A table describing the relationship between particular p and q values would be of little use since the manner in which they both relate to each other depends on the timeframe in which the new technology captures the entire market. The examples of market penetration curves shown in Figure 2.5 provide a few general principles regarding the effects of certain p and q value combinations. These examples are based on a 30-year timeframe which is typical of energy technology market penetration models.

2.2.5 Required Inputs

- Estimate the coefficient of innovation (p).

- Estimate the coefficient of imitation (q).

  This requires an estimate of three of the following four variables

  (a) t^* $\Rightarrow$ the time (year) when the technology's adoption rate is at its highest level (inflection point)

  (b) N^* $\Rightarrow$ the cumulative number of adopters at t^*

  (c) n^* $\Rightarrow$ the noncumulative number of adopters at t^*

  (d) m $\Rightarrow$ the population of adopters (i.e., market size).

- Since the information necessary for estimating the variables above is rarely available, the analyst could derive approximate p and q values from the market penetration curve of an established energy technology such as the natural gas combustion turbine.

- For a very rough estimate, the analyst needs expert judgment on the likely values of t^*, m, and the fraction of adoption occurring in the first or latter half of the adoption process.

2.2.6 Advantages and Disadvantages

The use of an innovation diffusion model certainly recognizes elements of market reality that a simple life-cycle cost comparison or "all-or-nothing" choice does not. The Bass Model provides a smooth s-curve for the rate of market penetration over time. Its chief advantage is its simplicity (once p and q are defined or assumed). This model is a sound forecasting tool as long as the parameters defining the proportion of "innovators" and "imitators" are defensible. This model has proved quite accurate given sufficient data for estimating the p and q values. It should be noted, however, that market researchers have tested the Bass Model more on the markets for consumer goods than for industrial technologies.

Even with defensible values for the coefficients of innovation and imitation, this model has several limitations. Once the p and q values are plugged into the algorithm, the s-curve forecast cannot account for any future changes in the market which may alter those values somehow. For example, the electric utility industry is undergoing significant structural changes which may alter the criteria governing its collective investment patterns over time. In addition, the Bass Model assumes that the innovation will capture all of the market at some time in the future. This may not always be the case. The analyst can avoid this problem by using the Bass algorithm to assign a "risk premium" to whatever cost measure is being used in comparing the new technology to its competing technologies. (See the summary of the Renewable Energy Penetration Model in Section 3.1 for details on this adaptation of the Bass Model. This problem can also be avoided by setting an upper limit on the percentage of the total market that the new technology can ultimately capture.

The Bass Model algorithm is little more than a means to draw an s-curve in the case of limited or no data for determining p and q values. This is not to say that it is entirely useless. The use of a justifiable industry or technology proxy lends some credibility to the use of this model. The model also lacks the ability to explicitly isolate the influence of certain factors which affect the market penetration rates of competing technologies. Several other market penetration models, particularly the Mansfield-Blackman Model and the NEMS, allow for the incorporation of particular market parameters.

Finally, the Bass Model suffers from being autoregressive. In an autoregressive model, the adoption of a technology in year t depends on the adoption of the technology in years t-1, t-2, and so on. Yet, the relationship between a technology's cost and its adoption by the market could possibly be nonlinear and discontinuous. Therefore, using such a logit function as the Bass algorithm to measure market share over time (years) rather than simply to adjust each year's measurement will yield incorrect results. The degree of error in doing so is debatable. Some model developers (e.g., those responsible for NEMS) believe that this characteristic leads to highly inaccurate predictions. Yet, the model has been shown to be quite accurate for some consumer durables (Mahajan 1990).

2.2.7 Best References

Bass, F. M. 1969. "A New Product Growth Model for Consumer Durables." *Management Science* 15:215-227.

Mahajan, V., E. Muller, and R. Srivastava. 1990. "Determination of Adopter Categories by Using Innovation Diffusion Models." *Journal of Marketing Research* 27:37-50.

Mahajan, V. and S. Sharma. 1986. "A Simple Algebraic Estimation Procedure for Innovation Diffusion Models of New Product Acceptance." *Technological Forecasting and Social Change* 30:331-345.

Schmittlein, D. C. and V. Mahajan. 1982. "Maximum Likelihood Estimation for an Innovation Diffusion Model of New Product Acceptance." *Marketing Science* 1:57-78.

2.3 The Mansfield-Blackman Model

Edwin Mansfield was one of the first economists to develop a model for forecasting an innovation's market penetration. In 1961, he published "Technical Change and the Rate of Imitation" which offered his theory on innovation diffusion. Ten years later, Wade Blackman further refined Mansfield's model and applied it to an innovation in the commercial aircraft jet engine market (Blackman 1971). Specifically, Blackman compared the model's forecast of the market adoption of a new jet engine with actual data to determine the accuracy of the model. Blackman concluded that the model's forecast "agreed well with 1) historical market share data related to the displacement of the turbojet engine by the first generation turbofan, and with 2) forecasts of future market shares related to the displacement of the first generation turbofan by the second generation turbofan." This model is most commonly referred to as the Mansfield-Blackman Model.

2.3.1 Key Concepts

Blackman made several major conclusions. The rate at which a new technological innovation displaces an existing product in a given market is an increasing function of the proportion of firms already using the new technology and the profitability of the new technology relative to the old technology, and is a decreasing function of the size of the investment required to adopt the new technology. His test results also led him to conclude that the propensity of an industry to innovate is related to the risk characteristics of the industry. Those industries which exhibit higher risk also exhibit a greater innovative propensity.

2.3.2 The S-Curve

The Mansfield-Blackman model yields an s-curve by using a logit function that is derived by a Taylor's series expansion. Equation 2.17 draws the s-curve, but the values that fill several key variables in the equation can only be found via the following chain of equations.

$$\Delta(t) = [m(t+1) - m(t)]/(L - m(t)) \tag{2.9}$$

$$\Delta(t) = f[m(t)/L, \Pi, S] \tag{2.10}$$

where $m(t)$ = market share captured at time t by the innovation which is displacing the old technology
L = upper limit on the market share which the innovation can capture in the long-term
$\Delta(t)$ = change in the market share achieved by the innovation between t and t+1
Π = profitability of employing the innovation
S = size of the investment required to install the innovation.

Change in the market share, $\Delta(t)$, increases as the market share increases, because as more information and experience are accumulated on the innovation, its adoption becomes less risky, and a "bandwagon" effect occurs. A Taylor's series expansion incorporates profitability (Π) and investment size (S) parameters to approximate $\Delta(t)$.

$$\begin{aligned}\Delta(t) = {} & C_1 + C_2[m(t)/L] + C_3\Pi + C_4S + C_5[\Pi m(t)/L] \\ & \rightarrow + C_6S[m(t)/L] + C_7\Pi S + C_8\Pi^2 + C_9S^2 \\ & \rightarrow + C_{10}[(m(t))^2/L^2] + \ldots\text{drop 3rd order}\end{aligned} \tag{2.11}$$

where C_i are coefficients and the variable terms were previously defined.

Substituting Equation 2.11 into Equation 2.9,

$$m(t+1) - m(t) = [L - m(t)] * [\text{Equation 2.11}] \tag{2.12}$$

For small time increments,

$$\begin{aligned} m(t+1) - m(t) &= dM(t)/dt \\ &= [L - m(t)] * [Q + \Phi(m(t)/L)] \end{aligned} \tag{2.13}$$

where Q = sum of all Equation 2.11 terms not containing $m(t)/L$
Φ = sum of all Equation 2.11 terms containing $m(t)/L$.

Equation 2.13 solution,

$$m(t) = \frac{L\,(\exp[I + (Q+\Phi)t] - Q/\Phi)}{1 + \exp[I + (Q+\Phi)t]} \tag{2.14}$$

where I = constant of integration
$\lim m(t) = 0,\ t \rightarrow -\infty \Rightarrow$ requiring $Q = 0$

With $Q = 0$,

$$m(t) = L[1 + \exp - (I+\Phi t)]^{-1} \tag{2.15}$$

Replace t with t' to get m(t'),

$$m(t') = L[1 + ((L/N_o)-1) \exp -\Phi t']^{-1} \tag{2.16}$$

where $t = t - t_1$ (i.e., current year - year 1)
$N_0 = m(t')$ at $t=t_1$ (i.e., the innovation's market share at the end of year 1)

Equation 2.16 can be rewritten to yield Equation 2.17 where the functional notation on m has been dropped. The Φ parameter governs the rate at which the innovation displaces the market share of the older competing technology.

$$\ln [m/(L-m)] = -\ln [(L/N_o) - 1] + \Phi t' \tag{2.17}$$

A quick way to find a value for Φ requires using inter-industry averages for both the payback period required to justify an investment and the average initial investment in the innovation as a percentage of the average total assets of the firm. Survey data on these criteria were fed into a regression analysis to yield Equation 2.18.

$$\Phi = Z + 0.530\Pi - 0.027S \tag{2.18}$$

where Z = (Z Factor), a relative, industry-specific constant corresponding to the risk associated with the industry (see Figure 2.6)
Π = profitability index which can be approximated by the average rate of return from the innovation divided by the cost of capital for the industry
S = investment index determined by the average initial investment in the innovation as a percentage of the total assets of the firms introducing the innovation.

These inter-industry averages were compiled in 1961. Therefore, the constants in Equation 2.18 (0.530 and 0.027) may no longer be valid. They are, however, a good starting point and the analyst can always use new inter-industry averages instead.

A relatively recent article by Nancy Rose and Paul Jaskow, entitled "The Diffusion of New Technologies: Evidence from the Electric Utility Industry," offers results of an application of the Mansfield-Blackman model to the electric utility industry. The article contains a table of values for a number of the parameters discussed above. Their work uses a form of the Mansfield-Blackman algorithm to predict an energy technology's market penetration rate over time.

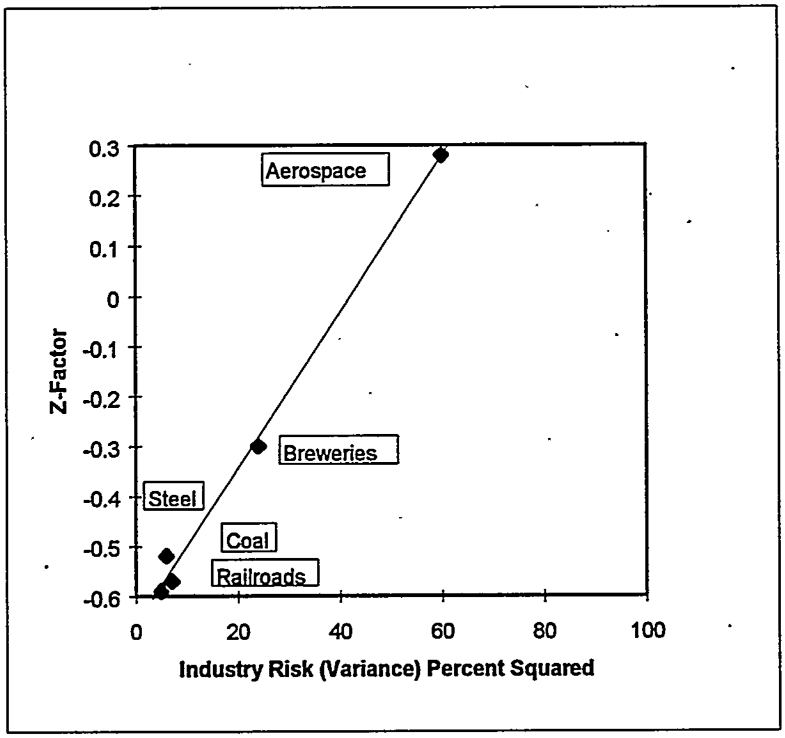

Figure 2.6. Z-Factor Index for Mansfield-Blackman Model

2.3.3 Required Inputs

- L ⇒ the upper limit on the market share which the innovation can capture in the long-term
- m ⇒ the size of the market
- Π ⇒ profitability index value, which can be approximated by the average rate of return from the innovation divided by the cost of capital for the industry; some applications of this algorithm substitute Π with a payback ratio which is the acceptable payback period divided by the expected payback period
- an industry-appropriate constant that is multiplied by the profitability index (0.53 is suggested)
- S ⇒ the investment index, which can be determined by the average initial investment in the innovation as a percentage of the total assets of the firm(s) introducing the innovation
- an industry-appropriate constant that is multiplied by the investment index (0.027 is suggested)
- Z ⇒ a constant between -0.6 and 0.3 corresponding to the industry's risk (see Figure 2.6)

2.3.4 Advantages and Disadvantages

The Mansfield-Blackman Model more explicitly addresses the issue of cost among competing options than does the Bass Model. Given defensible values for the variables in Equation 2.18, this model should be quite accurate. Both the Mansfield-Blackman and Bass Models rely on expert judgment to help determine the variable values for each set of equations. Historically, more analysis supporting variable definition has occurred for the Mansfield-Blackman model, although much of this is becoming dated and may no longer be valid. The electric utility industry's deregulation further adds to the prospect that these historic values may no longer be accurate when applied to utility markets.

Like the Bass model, this algorithm suffers from being autoregressive if used to forecast market penetration over multiple time periods. This problem is solved if the algorithm is applied only to adjust year-by-year estimates already generated by the model. See Section 3.2 on NEMS for more details on this approach.

2.3.5 Best References

Blackman, A. W. Jr. 1971. "The Rate of Innovation in the Commercial Aircraft Jet Engine Market." *Technological Forecasting and Social Change* 2:269-276.

Mansfield, E. 1961. "Technical Change and the Rate of Imitation." *Econometrica* 29 (4):741-766.

Laurmann, J. A. 1985. "Market Penetration of Primary Energy and its Role in the Greenhouse Warming Problem." *Energy* 10 (6):761-775.

Rose, N. and P. Joskow. 1990. "The Diffusion of New Technologies: Evidence from the Electric Utility Industry." *Rand Journal of Economics* 21 (3):354-373.

2.4 The Fisher-Pry Model

The Fisher-Pry Model is similar to the Bass Model. It also uses a logit function and the analyst must specify the year in which the innovation's market penetration is at its greatest rate of market adoption. In this model, that also means that the market penetration is half complete. A measurement of the innovation's market penetration in the "early" years is also necessary for applying the model's algorithm.

2.4.1 Key Concepts

The model is based on three assumptions: first, many technological advances can be considered as competitive substitutions of one method satisfying a need for another; second, if a substitution has progressed as far as a few percent, it will proceed to completion; and third, the rate of substitution of new for old is proportional to the remaining amount of the old left to be substituted.

2.4.2 The S-Curve

The Fisher-Pry Model's logit function works under the assumption that an innovation's market penetration grows at a constant exponential rate in the early years and its continued growth follows an s-shaped pattern. The simplest such curve is governed by two constants in the following equation:

$$f = (1/2)\ [1 + \tanh \alpha(t - t_0)] \qquad (2.19)$$

where α = half the annual growth in the early years

t_0 = time at which the innovation's market penetration reaches 50% of its total market share potential.

The Fisher-Pry Model specifies "takeover time" as the time required to go from f = 0.1 to f = 0.9 (fraction of the market). This span of time is inversely proportional to α. Therefore,

$$t = t_{0.9} - t_{0.1} = 2.2/\alpha \qquad (2.20)$$

which also can be written as,

$$f/(1 - f) = \exp[2\ \alpha(t - t_0)] \qquad (2.21)$$

This expression allows the analyst to plot the market penetration curve in the form of f/(1 - f) as a function of time on semilog paper and fit a straight line through the resulting points. The slope of the line is 2α, and the time t_0 is found at f(1 - f) = 1. The "takeover time" is measured between f = 0.10 and f = 0.9. Figure 2.7 provides an example of an s-curve derived by the Fisher-Pry algorithm.

2.4.3 Required Inputs

- $\alpha \Rightarrow$ the annual fractional growth rate of the technology's adoption (e.g., 5% per year) during its early years on the market; projected sales data for at least three to four of the first years on the market is helpful

- $t_0 \Rightarrow$ an estimate of the year in which the diffusion process will be half complete

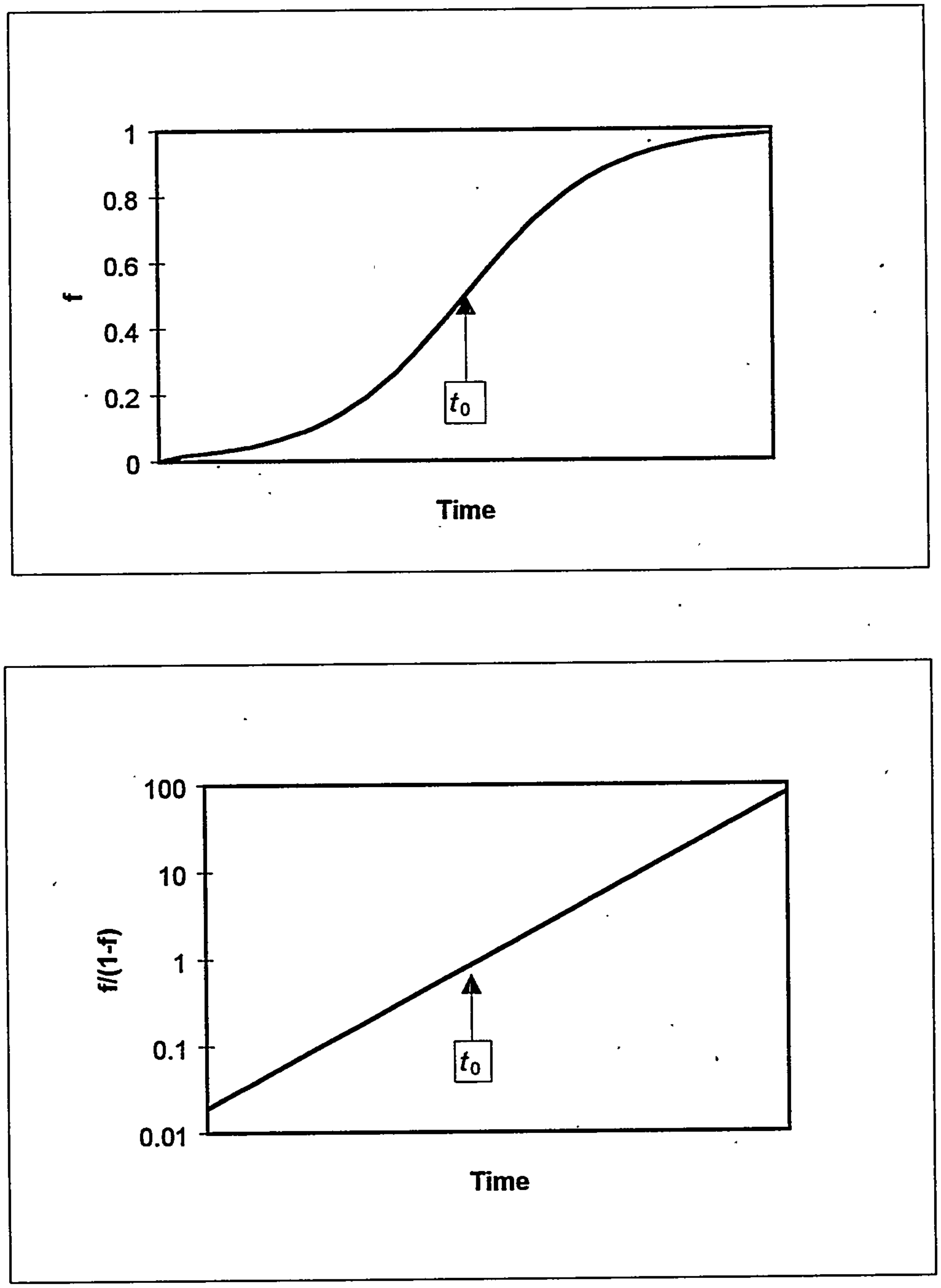

Figure 2.7. Fisher-Pry Market Penetration Curve

2.4.4 Advantages and Disadvantages

A clear advantage of the Fisher-Pry Model is its simplicity. It provides a smooth s-curve given knowledge or a good estimate of the growth rate in the technology's early years on the market and of the year in which its market penetration will be half complete. A mixture of a little data and expert knowledge is all that is required to generate an s-curve with this model. This model, however, generates a much less sophisticated forecast than do the Bass or Mansfield-Blackman models.

2.4.5 Best Reference

Fisher, J. C., and R. H. Pry. 1971. "A Simple Substitution Model of Technological Change," *Technological Forecasting and Social Change* 3:75-88.

2.5 A Meta-Analysis of Innovation Diffusion Studies

A meta-analysis conducted in 1990 by Fareena Sultan, John Farley, and Donald Lehmann combined the results of fifteen different innovation diffusion studies. The purpose of their effort was to identify notable patterns in the coefficients used among these diffusion algorithms. The authors used a weighted least squares analysis to account for many of the differences in the market environments addressed by each of the fifteen studies and the differences in approach used among them.

2.5.1 Key Concepts

The meta-analysis uses a number of special parameters to weight the p and q values in a way that more accurately accounts for variability in the research environment, model specification, estimation method, and data reuse. The results of their cross-study analysis were fed into the Bass Model's logit function to derive inter-industry, inter-technology values for the coefficients of innovation and imitation.

2.5.2 p and q Estimation

Both p and q are estimated using dummy variable regression, or analysis of variance, as expressed by Equations 2.22 and 2.23.

$$q_i = \mu + \alpha_1 X_{1i} + \alpha_2 X_{2i} + \beta_1 X_{3i} + \beta_2 X_{4i} \, YX_{5i} + \delta X_{6i} + \epsilon_i \tag{2.22}$$

$$p_i = \mu + \alpha_1 X_{1i} + \alpha_2 X_{2i} + X_{3i} + \beta_2 X_{4i} + YX_{5i} + \delta X_{6i} + \epsilon_i \tag{2.23}$$

where μ = regression intercept (p or q)
α_1 and α_2 = vector parameters addressing research environment
X_{1i} = the type of innovation (three levels: consumer durable, industrial/medical, and other)

X_{2i} = geographic effect (two levels: U.S. and Europe)

β_1 and β_2 = vector parameters addressing model specifications

X_{3i} = specification of a coefficient of innovation (two levels: present and absent)

X_{4i} = specification of marketing mix (two levels: present and absent)

Y = vector parameter for estimation method

X_{5i} = estimation method (three levels: ordinary least-squares [OLS], maximum likelihood estimation [MLE], and other)

δ = vector parameter for data reuse

X_{6i} = use of a particular dataset more than once in the meta-analysis (eight levels indicating repeated use)

ϵ_i = error term.

2.5.3 General Results of the Meta-Analysis

Across the 213 applications examined, the average coefficient of innovation (p) equaled 0.03, while the average coefficient of imitation (q) equaled 0.38. The average time at which a technology's adoption rate peaked (T*) was found to be 5.3 years. All of the individual values for these variables, however, varied widely. The authors found reported values of p ranging from 0.000021 to 0.03297 and values of q ranging from 0.2013 to 1.67260. In general, "industrial/medical" (utility technologies may be classified as such) products were found to have lower p values and higher q values than those representing consumer durables and other innovations. This suggests that potential adopters of an industrial innovation are more conservative in their investment decisions while they are also more likely forced by competitive pressures to imitate quickly.

The meta-analysis revealed the following significant effects in estimating the values of coefficients of innovation and imitation:

- *Effects Related to the Research Environment* - First, data from European countries produce higher coefficients of innovation principally because many of the technologies were introduced to the U.S. market first. Second, as noted above, industrial/medical innovations have higher coefficients of imitation than durables and other innovations.

- *Effects Related to Model Specification* - The presence of the coefficient of innovation produces a higher coefficient of imitation. Also, the presence of marketing mix variables leads to lower coefficients of imitation.

- *Effects Related to Estimation Technique* - The OLS method produces higher p and q estimates whereas the MLE method produces lower estimates of p and q.

To find the approximate duration of a technology's diffusion process, the authors used a basic form of the Bass Model equation for constructing the noncumulative adoption distribution:

$$T^{*} = (p + q)^{-1} \ln(q/p) \tag{2.24}$$

These authors suggest applying a Bayesian scheme for estimating the coefficients of innovation and imitation when only a few actual data points are available. Such an approach "mixes" the values derived from the meta-analysis with the actual data points. The authors claim that this produces a more reliable estimate since forecasts based on early data points are so susceptible to error.

Accounting for the broad effects uncovered by the meta-analysis may help the analyst adjust the regression equation parameters appropriately. Those parameters not needed in the analysis can just be set to zero.

2.5.4 Required Inputs

The equations used in the meta-analysis were developed to account for the variances in research environment, model specification, and estimation methods used among a set of innovation diffusion studies, including the Bass and Mansfield-Blackman approaches. An analyst would not use this meta-analysis approach unless a comparison of market penetration forecasts is needed. In such a case, the analyst needs to know or estimate values for as many of the above parameters as are necessary for accounting for the differences among the studies under comparison.

2.5.5 Advantages and Disadvantages

This meta-analysis of various market penetration studies does not offer a specific method for forecasting the market share of a given technology. Its purpose was to identify the similarities and differences of the various innovation diffusion approaches. This study effectively showed that the behavior of technology adopters varies significantly with the type of technology, and its intended market. The authors' findings serve as an important reminder to modelers of technology market penetration that p and q values are technology and industry specific.

For the lack of a defensible estimate for p and q values in using the Bass Model, the Meta-Analysis's interindustry averages may be useful.. At the very least, plugging these values into the Bass Model algorithm will show the rate at which the technology under examination would penetrate its market if it were a typical innovation in a typical market.

2.5.6 Best Reference

Sultan, F., J. Farley, and D. Lehmann. 1970. "A Meta-Analysis of Applications of Diffusion Models." *Journal of Marketing Research* 27:70-77.

3.0 Energy Technology Market Penetration Models

Four models that forecast the market penetration of technologies used by electric utilities either to produce power or for demand-side management (DSM) programs are examined in this section. The analysis of the REP model and NEMS is presented in greater depth because each is designed to forecast the market penetration of electricity supply-side technologies, which is of greater interest to OEM. The structure of these two models is also more adaptable to other technology penetration forecasting tasks than is the structure of the other two models which were designed specifically for DSM programs.

3.1 The Renewable Energy Penetration Model

The REP Model is a tool for forecasting the rate at which a set of selected renewable energy technologies will displace a portion of the competing conventional electricity generating technologies' market share. Princeton Economic Research, Inc., based in Rockville, Maryland, developed the model in 1993 for the DOE.

3.1.1 Adaptation of the Bass Model

The REP Model uses an initial risk level together with the Bass Model's market penetration algorithm as a "Risk Premium Factor" to adjust the levelized cost of energy (LCOE) over time for each intermittent and dispatchable renewable energy technology option. The effect of this adjustment is to raise the LCOE for each renewable energy technology by a decreasing amount over time in order to reflect the general rule that the perceived risk of a new technology decreases as it becomes more proven.

After the model calculates the LCOE's of all the technologies competing in a given market, it applies the following algorithm to adjust the LCOE of the renewable energy technologies over time:

$$\text{Current Risk Premium} = \text{Initial Premium} + (\text{Final Premium} - \text{Initial Premium}) * \frac{1 - e^{-(p+q)t}}{1 + (q/p)e^{-(p+q)t}} \qquad (3.1)$$

Higher values for p increase the amount of adoption in early years, whereas higher values for q increase adoption in later years. The Initial Risk Premium (%) represents the starting level of perceived risk for the new technology. For example, if the analyst estimates the added perceived risk of a wind system is 50%, then a value of 1.50 is entered. The Final Risk Premium should be set to 1, if the analyst assumes the risk premium for the technology will drop to zero by the end of the analysis period. Figure 3.1 presents the effect on market share of using the Bass algorithm to adjust a technology's risk premium over time versus reducing its risk premium linearly.

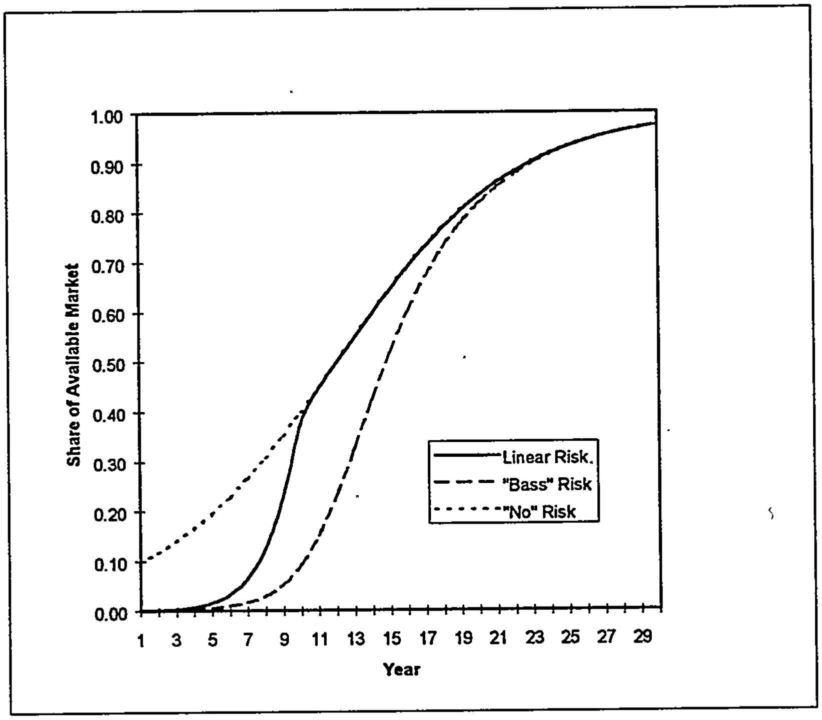

Figure 3.1. Effects of Alternative Risk Premiums on Market Share

3.1.2 Market Share Calculation for Intermittent "Fuel Saver" Renewable Energy Technologies

The REP Model treats intermittent, or "fuel saver," technologies differently than it treats dispatchable technologies. Consequently, their respective market shares are also calculated in slightly different manners. The REP Model follows the series of steps summarized below to forecast the market penetration of fuel saver (intermittent) technologies.

Steps - Intermittent Technologies

1. Calculates the value of the energy displaced by the renewable energy (RE) system. This is a linear interpolation based on the conventional technologies' LCOEs calculated for the first and final years of the analysis.

2. Calculates the size of the potential market.

3. Calculates the limits on how much RE can be installed per year. This includes the industry's ability to supply the technology, resource availability, and grid share limit.

4. Calculates the risk-adjusted LCOE for the RE system. This is the application of the Bass Model algorithm. The Bass equation governs the rate at which the risk premium declines over time.

5. Calculates the Economic Attractiveness Ratio (EAR) to determine an initial estimate of the RE system's market share. The EAR is the ratio of the risk adjusted LCOE of RE to the marginal cost of conventional energy. The REP Model then applies this EAR to a set of scaled EAR preference levels called the Financial Attractiveness Relationship (FAR) table. The FAR represents the percentage of decision makers in a given market who would select a new technology at a given EAR level. For each EAR level, there is a corresponding FAR value, which represents the percentage of the market a RE technology can potentially seize at that price ratio.

6. Calculates an initial estimate of the RE technology's market share and the corresponding electrical energy generation displaced. A technology's FAR actually represents a relative score which captures a limit-prescribed percentage of the market. Equation 3.2 translates the FAR scores into market share.

$$\text{Market Share}_A = \text{Score}_A \ / \ (\text{Score}_A + \text{Score}_B + \ldots \text{Score}_n) \tag{3.2}$$

7. Recalculates the estimated LCOE to verify that the first iteration is reasonable and accounts for uses of lower quality resources as more are used.

8. Processes the estimate through a series of checks to ensure that particular limits are not surpassed.

3.1.3 Market Share Calculation for Dispatchable Renewable Energy Technologies

The market for dispatchable load is apportioned among competing technologies in proportion to the LCOE of each. The REP Model uses the following steps to calculate the market allocation among the competing dispatchable technologies.

Steps - Dispatchable Technologies

1. Calculates the market size for peaking, intermediate, and baseload.

2. Calculates the LCOE of each competing technology.

3. Applies the risk premium to adjust the LCOE (in $/kWh) of the technology. The calculations vary by technology. The analyst defines an Initial Risk Premium and the decline in that risk over time is governed by the Bass equation.

4. Calculates market share allocations. Once each technology's LCOE has been adjusted for risk, a logit function is applied to allocate market share among the alternatives based on their score. The function is not based on any innovation diffusion theory, but serves merely as a means for allocating market share among the alternatives.

$$\text{Market Share}_{\text{Tech A}} = \text{LCOE}_A^{-\lambda} / (\text{LCOE}_A^{-\lambda} + \text{LCOE}_B^{-\lambda} + \ldots\text{LCOE}_n^{-\lambda}) \tag{3.3}$$

The exponent (λ) in Equation 3.3 is simply a means to allocate market share among the alternatives. This value usually lies between 0 and 16. The documentation for NEMS assigns a value of 10 as the appropriate λ for the energy market (assuming that costs are independent and the cost of each technology follows a Weibull distribution). A check should be applied to ensure that an assigned market share is not smaller than the smallest size technology x plant. The value of λ determines how quickly a particular technology's cost advantage translates into its increasing share of the market. Higher values for λ increase the share that the lower cost technologies will receive.

5. Calculates initial capacity estimates based on market share and annual market requirements (load growth and replacements).

6. Calculates adjustments to the estimated capacity calculated above. This includes adjustments for industry capacity limits and resource availability limits. Any excess of a technology's limit is then allocated to the remaining options.

3.1.4 Required Inputs

The purpose of examining the REP model here is to describe its general structure rather than to pay special attention to the unique features attributable to forecasting RE resources and technologies. Of course, use of the REP model requires the analyst to input a number of renewable resource- and technology-specific data. Step #5 in the process to forecast the market share of intermittent RE technologies requires the use of financial attractiveness ratios. Since the need for such ratios is unique to these technologies, the list below does not include an item for this information. The analyst must know or estimate the following list of items when using a model of similar structure to the REP model regardless of energy resource or technology type.

- Input the marginal cost and performance of the competing technologies. This requires

  (a) capital cost of plant and equipment and the rate and duration in the decrease of those costs

  (b) operating cost and the rate and duration in the decrease of those costs

  (c) proper technology-specific discount rate to use in the financial calculations determining the LCOE of the technology.

- Estimate the market size; REP does so by load segment and by Federal region
- Estimate the technology manufacturing industries' ability to supply demand over time (i.e., technology manufacturing limits)
- To establish an Initial Risk Premium, estimate the sum total of all "other" risk factors not accounted for in the technology-specific discount rate used in the financial calculations. This may implicitly include several factors which typically increase the cost of an immature technology.
- Choose appropriate values for the coefficients of innovation (p) and imitation (q) used in the Bass algorithm logit function.
- Choose a value for the logit function using the exponent (λ).

3.1.5 Advantages and Disadvantages

The REP Model mixes the Bass Theory with the NEMS model approach (see Section 3.2) in allocating market share among the competing technologies. The model incorporates the concept of innovation and imitation through its use of the Bass principles as well as the means to allocate market share among the alternatives by using the logit function also used in NEMS and FOSSIL-2. The effects of the two logit functions do not confound each other because the Bass function affects only the LCOE of the technologies while the other logit function allocates market shares based on the costs of the technologies. NEMS does not incorporate the concept of innovation and imitation in its market sharing algorithm.

The REP model allows the analyst to treat the issues of technological risk in a very open manner. The analyst can choose (with expert judgment) which risk issues to address and what initial weight to give them collectively. The control over how these issues are treated over time, however, is somewhat limited. Only through the initial prescription of three values (an added risk premium and the choice of specific p and q values) can the analyst account for the various elements that make a new technology risky in the early years and mature over time. Despite this loose control, it is a broadly accepted theory that governs the rate at which a new technology's perceived risk, and hence its cost, declines over time. As is more thoroughly explained in the next section, NEMS also requires the analyst to estimate three conditions affecting a technology's cost over time: a technological optimism factor, the effect of learning, and effects of leadtime risk. Thus, NEMS recognizes three specific factors as the forces which drive a new technology's increased acceptance over time, while the REP Model allows any number of factors to be collectively addressed via a single adjustment mechanism.

The REP Model does not come with prescribed p and q values. A combination of the unique nature of many new energy technologies and the lack of prescribed p and q values for industry proxies requires that the model's user do the research for choosing appropriate values. The analyst must also determine the level of initial risk to input at $t=0$. These three values can only be determined through expert judgment.

3.1.6 Best References

Bass, F. M. 1969. "A New Product Growth Model for Consumer Durables." *Management Science* 15:215-227.

Mahakan, V., E. Muller, and R. Srivastava. "Determination of Adopter Categories by Using Innovation Diffusion Models." *Journal of Marketing Research* 27:37-50.

U.S. Department of Energy. 1993. *Renewable Energy Penetration Model - Final Report*. Washington, D.C.

3.2 The National Energy Modeling System (NEMS) (Electricity Market Module)

NEMS improves upon past Energy Information Administration technology penetration forecasting models because it more directly addresses several key issues of technological risk associated with *new* technologies. The model also more explicitly incorporates cost changes as the new technology matures over time to account for "learning-by-doing" and the consequent gradual industry acceptance of a new technology. NEMS incorporates an important concept in the technology maturation process by having the annual changes in a technology's cost be dependent on the market share it receives. A new technology can achieve market "lock-in" when its relative competitiveness allows it to steadily penetrate more of the available market at the expense of competing technologies. The more market share it gains, the faster its cost reduces. A technology which does not reduce its cost quickly enough will eventually get "locked-out" of the market.

3.2.1 General Structure

NEMS' market penetration model is made of three main parts. First, the model generates a marginal cost ($/kW) for each technology for year (t). In this stage, the model adjusts the input estimates on cost and performance to ensure consistency in determining capital cost, and to account for the effects of technological optimism and learning on a technology's marginal cost at that time. Second, the model uses a linear program (LP) to rank and choose the technologies which will fill the needed capacity at the lowest cost. Finally, the NEMS market sharing algorithm uses a logit function to reallocate market share among the top set of technologies considered, but not necessarily chosen by the LP model.

3.2.2 Part 1: Initial Catalog of Costs and Performance

The first input into the model is the estimated marginal cost of the new technologies. The model addresses four major issues regarding these cost estimates. First, it ensures that the installed cost estimates are derived in an internally consistent manner. This is of particular concern for those projects with a long leadtime. Inflation and interest charges during the plant's construction complicate the derivation of an installed cost. To derive an installed cost for a plant that typically takes years to construct, the model uses a cash profile curve to derive an appropriate cash outlay figure to use in determining the technology's initial marginal cost. Second, the model accounts for the possibility that the "overnight" cost estimates are tainted by technological optimism. Third, a technology's marginal cost is adjusted for each successive year to account for the learning that stems from increasing market penetration. Fourth, an adjustment to the discount factor is used to account for the risks associated with the technology's leadtime.

Technological Optimism

The phrase "first-of-a-kind" describes a new technology with highly uncertain cost and performance characteristics. NEMS lends special attention to first-of-a-kind technologies as opposed to the cost and economics of "n^{th}-of-a-kind" technology. First-of-a-kind technology cost and performance estimates are typically too low due to "technological optimism." Recent research suggests that the closer the new technology is toward commercialization, the less will be the underestimation of costs (Merrow 1981). Two principles guide the model's treatment of this problem. The more a new technology departs in character from the previously established commercial technologies, the greater the disparity between the cost estimate and the actual cost. Also, as the completeness of the design increases, the difference between the estimated cost and the actual cost decreases. A regression equation based on these two principles provides the analyst with a contingency factor to apply to the overnight cost estimates (see Equations 3.4 and 3.5).

The NEMS algorithm treating technological optimism assumes that such optimism affects a specified number of future units and that it will decrease linearly until the actual and estimated costs are the same. The model derives the number of operational units by dividing the available capacity for the technology in question (by year) by the typical unit size. The slope of the line that denotes the decrease in technological optimism is given by

$$Slope_{Tech\,A} = (1 - TECHOPFAC_{Tech\,A}) \,/\, (UNITSN_{Tech\,A} - UNITSOP_{Tech\,A}) \tag{3.4}$$

where $TECHOPFAC_{Tech\,A}$ = initial technological optimism factor
$UNITSN_{Tech\,A}$ = number of units of capacity of technology (A) completed when technological optimism is no longer observed
$UNITSOP_{Tech\,A}$ = number of units of capacity of technology (A) completed corresponding to initial technological optimism factor

The technological optimism factor for Technology (A) in a given year (Y) is then found by

$$TECHOPFAC_{Y\,Tech\,A} = TECHOPFAC_{Tech\,A} + SLOPE_{Tech\,A} * UNITS_{Y\,Tech\,A} \quad (\text{for } UNITS_{Y\,Tech\,A} \leq UNITSN_{Tech\,A}) \tag{3.5}$$

where $UNITS_{Y\,Tech\,A}$ = number of units of capacity of technology (A) completed by year (Y) in excess of $UNITSOP_{Tech\,A}$.

One important caution the analyst should take when setting the value of this parameter is to ensure that the initial cost and performance estimates have not already been adjusted to account for technological optimism or other factors, such as risk. The model will, of course, underestimate a technology's market share if its "new technology" cost premiums are imposed twice.

The Learning Effect

With all factors held equal among competing technologies, the costs of technological innovations will fall through the progression from first-of-a-kind technology status to the n^{th}-of-a-kind stage. NEMS' developers recognized five major attributes which contribute to this common pattern:

- *Learning-by-Using* - The more a technology is used, the more is learned about it and, therefore, the more it is improved.
- *Network Externalities* - The availability of products and services related to the new technology increases over time.
- *Production Economies of Scale* - The cost of the new technology's components falls as more units are sold.
- *Informational Increasing Returns* - A technology that is more widely adopted is often better understood and more attractive to risk-averse adopters.
- *Technological Interrelatedness* - As a technology becomes more widely adopted, a number of subtechnologies, products, and services become part of its infrastructure.

NEMS applies a log linear function to incorporate the effects of learning on a new technology's cost and performance over time. This function applies a decrease in costs by a constant percentage for each doubling of the technology's cumulatively installed capacity. The learning effects algorithm uses the following equations.

$$C_N = C_1 * N^b \tag{3.6}$$

where C_1 = cost of first generating unit ($/kW)
C_N = cost of Nth generating unit ($/kW)
N = number of units currently completed.

Letting N = 2 (i.e., considering a doubling of capacity between the first and second units) allows the analyst to find a value for the exponent b. Note that b is negative so that as N increases the corresponding cost decreases.

$$b = \ln(1 - LCR) / \ln(2) \tag{3.7}$$

where LCR = cost reduction for every doubling of capacity (fraction).

Cost reductions proceed as follows:

$$C_2 = C_1 * 2^b; C_4 = C_1 * 4^b; C_8 = C_1 * 8^b \tag{3.8}$$

These cost reductions continue until the number of units completed reaches a prescribed level where the learning-by-doing effect no longer affects the development or performance of that particular technology. At this stage, the technology would be called an "n^{th}-of-a-kind" technology. The learning factor (LF) associated with the Nth unit ($N < n$) is expressed as a multiplier of C_n. The LF_N describes the decrease in capital costs between the Nth-of-a-kind and nth-of-a-kind units for a maturing technology.

$$C_N = C_n * LF_N \tag{3.9}$$

$$LF_N = (N / n)^b \tag{3.10}$$

The learning factor is set to 1.0 once the cumulative capacity reaches the prescribed number of units necessary for the technology to attain "n^{th}-of-a-kind" status.

Leadtime Risk Adjustment

After the model has adjusted the marginal cost of each technology to account for technological optimism and the learning effect, it further adjusts those costs to reflect the risks associated with each technology's leadtime. The relationship between risk and a technology's leadtime is quantified through an adjustment to the discount factor used in measuring the present value of the fixed and variable costs of each technology.

The capital costs of long-leadtime technologies will be more sensitive to changes in such exogenous factors as interest and inflation rates. These technologies also suffer from the increasing degree of uncertainty about future electricity demand. Therefore, the capital costs of long-leadtime technologies are more uncertain than those technologies which can be installed more quickly. The model treats this kind of risk by varying the discount rate to match the technology's relative leadtime. This is commonly known as the adjusted discount rate method. Those technologies perceived to be riskier because of their long leadtime will have their discount rates adjusted downward. This might seem counter-intuitive, but the model is comparing future costs, so lowering the discount rate results in a capital cost premium. Although the NEMS developers state that the certainty-equivalent method is a more appropriate approach they chose to use the risk-adjusted discount factor method instead because it is by far the more widely used capital budgeting approach.

A second leadtime-related risk incorporates the uncertainty which accompanies decisions that are irreversible once made. No one has yet developed an empirical approach to quantify a "value-of-waiting" factor for the utility industry. The NEMS documentation, however, suggests that technologies with a short leadtime enjoy an economic advantage because they allow a utility to wait for more accurate information about future demand.

At the time this report was written an algorithm for leadtime-related risk has not been incorporated into NEMS. The lack of data on the effect of leadtime on risk has put the inclusion of this factor on hold. Consequently, the discount rates affecting each technology are currently set to the same value.

3.2.3 Part 2: First Pass Choice of Technologies

Once the cost adjustments described above are completed, an LP ranks each technology according to its cost profile and chooses the least-cost technologies to fill the needed capacity. First, the model borrows from the ECP submodule's forecast of how much capacity is needed by load segment. This forecast is derived from per-year load growth and plant retirement estimates for each of the ten Federal regions divided into fuel type and plant owner groupings.

Next, an LP routine determines the best mix of technologies to meet the needed capacity. Each technology is then ranked according to its cost competitiveness in each load segment. This "all-or-nothing" choice, however, does not reflect real market behavior. Therefore, a market-sharing algorithm is used to reallocate market share among the most competitive set of technologies.

3.2.4 Part 3: Market-Sharing Algorithm

NEMS uses a logit function to correct the "all-or-nothing" decision arrived at by the LP model. This algorithm allocates a portion of the market to technologies that were not chosen by the LP model. In this market allocation function, technologies penetrate the market according to the following ratio of marginal costs.

$$MS_i = \frac{MC_i^{-\alpha}}{\sum_{i=1}^{i=n} MC_i^{-\alpha}}, \; i = 1,\ldots,n \tag{3.11}$$

where MS_i = market share for the ith technology
MC_i = marginal cost for the ith technology
α = exponent of the logit function.

Note the similarity between Equation 3.11 and Equation 3.3, which is used by the REP model. The value of α determines how quickly a particular technology's cost advantage translates into its increasing share of the market. Higher values for α increase the share that the lower-cost technologies will receive. While the NEMS documentation suggests using a value of (10) for α, there is little evidence to suggest that one value for α is better to use than another. As explained in Section 3.1.2 of the REP Model summary, this logit function was not borne of any innovation diffusion theory. It is simply a mathematical tool to reapportion the market among the competing technologies.

The LP described in Section 3.2.3 calculates and stores the ratio of a technology's actual cost to the cost required for it to be the top choice. Technologies with a cost ratio exceeding a user-defined limit are dropped from further consideration. The surviving technologies are then allocated a market share using Equation 3.11. These market shares are then used to reallocate the total capacity additions determined by the LP model's first pass choice of technologies. The revised model decision is given by

$$BLD_{yc} = MS_{yc} * TOTBAS_y \tag{3.12}$$

where BLD_{yc} = market-sharing build decision for capacity type c beginning in year y
MS_{yc} = market-sharing for capacity type c beginning in year y
$TOTBAS_y$ = total market in year y.

For example, if the ECP model forecast calls for 500 MW of new capacity, the LP model may choose to fill that need with 300 MW generated by technology X and 200 MW from technology Y. Then, the logit function allocates 100 MW to technology Z by virtue of its marginal cost being within a predefined factor above the least-cost alternative(s). To ensure that the model does not then allocate more capacity than is needed by the market, two more steps readjust the original LP model allocations downward and in proportion to their relative costs. Now, technology X is given 266 MW, technology Y is given 134 MW, and technology Z is allocated 100 MW to meet the need for 500 MW of capacity.

3.2.5 Outline Summary of NEMS Technology Penetration Model

I. Develops the initial catalog of costs for competing technologies.

   A. Adjusts overnight construction cost estimates to account for interest and escalation during the planning and construction period.

   B. Adjusts costs (up) for technological optimism.

   C. Adjusts costs (down) for learning.

D. Adjusts costs (up) for leadtime risks:

   1. Risks due to variations in cost,

   2. Risks due to variations in capacity demand.

II. Determines the choice of technologies.

   A. LP model determines the technologies used to meet a given segment of demand (e.g., baseload, intermediate, or peak).

      1. Determines the needed amount of capacity (i.e., market size).

      2. Determines the least-cost mixture of technologies to meet the needed capacity.

   B. Applies logit function to determine the market share among the competing technologies.

      1. Determines market share for each technology and total units to be built for a given year.

      2. Adjusts LP capacity expansion decisions (down) to account for reallocation among the technologies granted some market share by the logit function.

This process is then repeated for subsequent years.

3.2.6 Required Inputs

The analyst must provide the following to allow the model to calculate the market shares of competing technologies:

- The marginal costs, at t=0, of the competing technologies; this includes the "n^{th}-of-a-kind" overnight construction costs (fixed costs) and annual operating costs (variable costs) of generating power. These initial cost and performance estimates should not include a risk or technological optimism premium.

- The average leadtime for the technology to go online and the cash outlays per time period (e.g., by quarter or year). This information is used to calculate interest and escalation during construction and to adjust the technology's present value calculation to account for leadtime risk.

- An initial contingency factor (e.g., a 20% addition to the marginal cost at t=0) to account for the optimism often associated with estimates for new technologies and the number of future units for each of the new technologies which will be affected by technological optimism. The technological optimism factor will decrease linearly as each of those specified number of units is built.

- The learning effect cost reduction (fraction) for every doubling of the new technology's capacity and the number of units of the new technology that must be built in order for the learning effect to no longer impact cost.

- The market size; NEMS estimates the future market for electricity by load segment and by Federal region.

- The logit function's exponent (α).

3.2.7 Advantages and Disadvantages

NEMS is the most complete of the market penetration forecasting methods reviewed herein. It stands alone in explicitly addressing the issues concerning leadtime, technological optimism, and the effects of learning. All of these concerns are important to recognize in distinguishing new technologies from conventional ones. Other models contend with risk through cost multipliers of some sort, but do not give the analyst much precision in controlling the impact of the various elements affecting the cost of new technologies. The NEMS method does allow such precision. The analyst must be careful, however, to ensure that initial cost and performance estimates are not already adjusted upward to account for the factors included in the technological optimism adjustment.

The logit function in NEMS is only used as a means to reallocate market share among the alternative technologies each year to correct for the unrealistic results generated by the "all-or-nothing" decision of the LP model. The logit function is not used to directly predict market share over a multiyear timeframe, and thereby avoids the autoregression problem. In theory, this approach should provide a more accurate long-range forecast.

By not using the Bass algorithm, the NEMS market sharing algorithm avoids the problems associated with finding proper values for the coefficients of innovation (p) and imitation (q). Yet, the model ignores the worthy concepts of innovation and imitation underlying the Bass innovation diffusion theory. On the other hand, NEMS captures the concept of market "lock-in" and "lock-out."

NEMS, by eliminating those technologies with intolerably high cost ratios, does not consider the real possibility that an immature technology can achieve cost reductions and performance improvements through R&D. Cost reductions do accrue through learning, but the estimated mature cost is a fixed assumption.

NEMS' model structure is simple enough to be used for less complicated spreadsheet forecasting constructions. The structure, however, is more difficult to build than is the REP model's form. The need for an LP decision tool within the model adds a level of complexity that other applications do not have. This model structure also carries with it the probability that its use in other modeling efforts will receive wider acceptance and credibility since the NEMS is currently one of DOE's primary forecasting tools.

NEMS' method does leave the analyst open to defending several input estimates. First, the initial level of the technological optimism factor, its rate of decrease, and its duration must all be derived by expert judgment. Second, the factors governing the learning effect must also be based on expert judgment. Finally, the value of the logit function's exponent (α) must also be assumed. Neither the NEMS documentation nor other market research effort offers evidence that using one particular α value conveys a more accurate representation of buyer behavior than does another value. Perhaps the only way for the analyst to compensate for this weakness is to clearly document the consistent application of the exponent across all competing technologies.

3.2.8 Best References

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3.3 The Assessment of Energy Technologies (ASSET) Model

ASSET is a commercially available software package designed by Regional Economic Research, Inc. This software was designed primarily for forecasting the adoption of technologies relevant to utility DSM programs. It is, however, flexible enough to be adapted for measuring the market penetration of power supply technologies.

3.3.1 Key Concepts

The adoption rate models within the ASSET program are logit function tools which give adoption rates and market shares as functions of technology option characteristics and energy consumer behavior. The variables accounting for end-use consumer behavior can be altered to reflect the utility industry's buying behavior. ASSET offers three types of logit function systems; *binary*, for one-on-one technology comparisons; *multinomial*, for comparing an array of technologies; and *nested*, a more detailed form of the multinomial system.

3.3.2 Adoption-Rate Models

Binary Logit Systems

In its simplest form, a binary logit system gives the share for an option as a function of the characteristics of that option and a single competing option. The shares for two competing options are given as follows:

$$Share_1^t = \frac{\exp(a_1 + bX_1^t + c_1Z^t)}{\exp(a_1 + bX_1^t + c_1Z^t) + \exp(a_2 + bX_2^t + c_2Z^t)} \tag{3.13}$$

$$Share_2^t = \frac{\exp(a_2 + bX_2^t + c_2Z^t)}{\exp(a_1 + bX_1^t + c_1Z^t) + \exp(a_2 + bX_2^t + c_2Z^t)} \tag{3.14}$$

Constant Term

The option-specific constants (a_1 and a_2) represent the average influence of all excluded factors. For example, if the explanatory variables relate to cost characteristics of an option, then the constant will capture the positive or negative impacts of the non-cost characteristics.

Option Characteristics

The X variables represent characteristics of the options, which can include cost and non-cost attributes. The slope coefficients determine the sensitivity of the share results to the value of each attribute. For example, if the X variables include first cost and operating cost, then the corresponding slope coefficient (b) gives the sensitivity of the option share with respect to these cost variables.

Buyer Characteristics

The Z variables represent buyer characteristics. Since buyer characteristics may be positively correlated with some options and negatively correlated with other options, the slope coefficients (c_1 and c_2) have option subscripts.

This binomial logit function can be rewritten to specify a technology's market share with respect to the relative attractiveness of that technology. In this form, $a = a_2 - a_1$ and $c = c_2 - c_1$; the X variables enter as incremental cost or savings for the second option relative to the base option.

$$\mathrm{Share}_2^t = \frac{\exp(a + b(X_2^t - X_1^t) + cZ^t)}{1 + \exp(a + b(X_2^t - X_1^t) + cZ^t)} \tag{3.15}$$

Another form of this binary system uses a payback (PB) measurement as the X variable:

$$\frac{\exp(a + b * PB^t)}{1 + \exp(a + b * PB^t)} \tag{3.16}$$

Since the PB measure is widely used for purchase decisions involving energy efficiency technologies for the residential and commercial sectors, this function may be particularly useful for forecasting the market share of many end-use energy technologies. The binary logit function based on PB is illustrated in Figure 3.2.

Multinomial Logit Systems

The multinomial logit is a generalization of the binary logit, and applies to situations where there are more than two outcomes. This type of model can be used to compute purchase probabilities or shares for

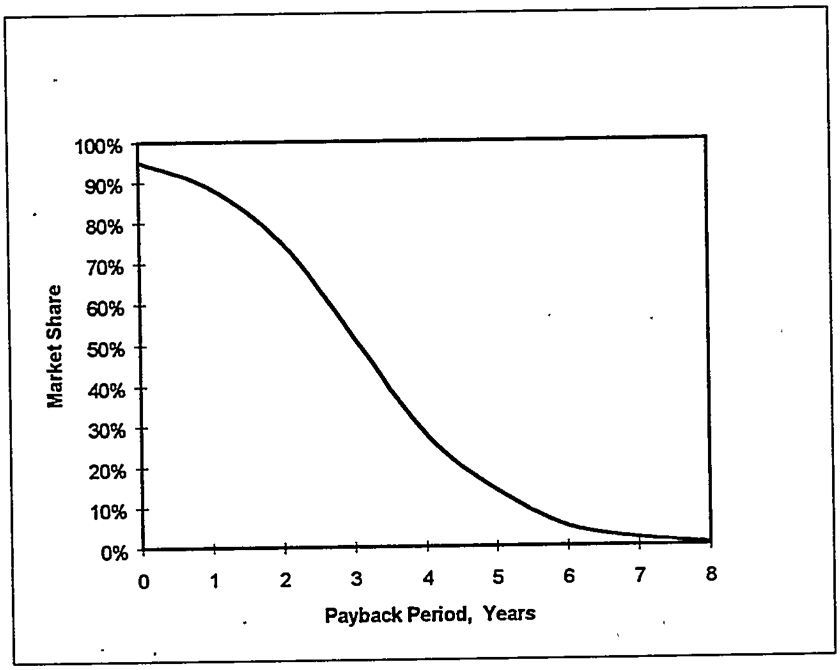

Figure 3.2. Example of Binary Logit Curve Using Payback

a group of competing options. Each option has an "attractiveness" equation that includes cost and non-cost attributes of the option. The form of the multinomial logit gives the share of an option as the attractiveness function for that option divided by the sum of the attractiveness functions.

$$\text{Share}_i^{\,t} = \frac{\exp(a_i + bX_i^{\,t} + c_i Z^{\,t})}{\Sigma_j \exp(a_j + bX_j^{\,t} + c_j Z^{\,t})} \tag{3.17}$$

The definition of the multinomial constant term, option characteristics, and buyer characteristics is identical to that of the binary logit system.

Nested Logit Systems

Nested Logit models are similar to multinomial logits, but additional structure is imposed on the substitution patterns among the competing options. This type of function is most effective at comparing closely competing technologies within closely competing groups of technologies.

3.3.3 Required Inputs

As for any market penetration model, the analyst must input the data governing the applicable market as well as the cost and performance of the technologies. The ASSET Model, however, requires a number of estimates unlike those of other market penetration models. The analyst must estimate the following:

- the average influence of all excluded factors (a positive or negative multiplier); "excluded" factors refer to those issues not accounted for by the explanatory variables X and Z

- the sensitivity of each technology to the cost and non-cost characteristics represented by the variable X; these may include fixed and variable costs, regulatory costs, jobs, etc.

- a number of buyer characteristics and the corresponding sensitivity levels of those characteristics with respect to specific technologies

- the PB ratios preferred by the intended market with respect to given sizes of investment.

3.3.4 Advantages and Disadvantages

Given enough data, the logit functions used in the ASSET software are effective forecasting tools. The analyst, however, has to obtain a sufficient amount of historical data in order to determine appropriate values for the a, b, and c coefficients in each of the equations. For forecasting the market growth of new energy technologies that are still in the R&D stage, it would be difficult, if not impossible, to collect sufficient data to run the statistical processes required to determine those values.

The algorithms of the ASSET package enable the analyst to explicitly account for the cost and non-cost factors that affect the distribution of a technology's adoption over time. Since these algorithms use historical data to effectively explain the patterns of market adoption in the past, they are quite good at forecasting. Therefore, when the analyst has enough data to use a maximum likelihood, or least-squares method to find appropriate values for these binary or multinomial logit functions, this can be an effective tool. A particular advantage of this approach over several other algorithms, such as the purely applied Bass, Mansfield-Blackman, and Fisher-Pry theories, is its ability to apportion market share entirely on the relative merits of the competing technologies. It does not assume that the new technology will ultimately capture the entire market.

3.3.5 Best Reference

Regional Economic Research, Inc. 1995. *ASSET User's Guide*. San Diego, California.

3.4 The Market TREK Model

The Market TREK software was designed by the Research Triangle Institute for EPRI to help its members build more effective DSM programs. It was designed exclusively to forecast the market penetration of DSM technologies.

3.4.1 Key Concepts

Market TREK contains three principle models for predicting market penetration. The *Chain Ratio Models* are screening measures for estimating market size in a particular market or segment. The *Adoption Process Models* simulate customers' movement through the decision making process and then forecast the time path of technology adoptions. These models are good for "what if" scenarios and also allow for marketing-mix analysis. The *Diffusion Models* forecast adoptions over time. These models are particularly useful in the early stages of the product life-cycle, when limited data are available. These models are based on three diffusion models: Bass, internal-influence, and Horsky-Simon.

3.4.2 General Capabilities

The Market TREK model has four general capabilities:

1. Forecasts the number of customers in the market for a technology, program, or service.

2. Forecasts the influence of marketing activities and program characteristics on the size of the market for a technology, program, or service.

3. Forecasts the number of customers who will purchase a technology, join a program, or adopt a service over time.

4. Forecasts the influence of marketing activities and program characteristics on the speed with which customers adopt a technology, program or service.

3.4.3 Required Inputs

An extensive survey of end-use customers was conducted to obtain the necessary values to use in the diffusion models. Since this software was designed primarily to analyze the end-use market, these values may be of little use for modeling the market penetration of power supply technologies.

3.4.4 Advantages and Disadvantages

This model may be very good for forecasting the market penetration of end-use energy technologies. It is of little use for forecasting the market diffusion of energy generation, storage, transmission, or distribution technologies, however. Its process for determining market penetration rates is not flexible enough to convert the focus from end-use to energy supply technologies.

3.4.5 Best Reference

Electric Power Research Institute. 1992. *Market TREK, Volume 2: Guide to Market penetration Forecasting*. Palo Alto, California.

4.0 Conclusions and Recommendations

A market penetration model should produce a forecast which reflects patterns of real market behavior. While a technology with superior characteristics may capture 100% of a market, this would be an unusual situation. More commonly, two or more technologies with moderately different characteristics will share a market, even when one technology may appear superior based on average conditions. Variations in product characteristics and consumer preferences for a given set of characteristics explain this phenomena. Thus, a market penetration model must explicitly or implicitly consider the variability or uncertainty surrounding a technology adoption decision. All of the innovation diffusion theories and market penetration models described in this report implicitly address uncertainty via a logit function. A logit function is easier to use and accomplishes essentially the same result as an explicit treatment of uncertainty. Therefore, the logit function is generally recommended. Still, the logit function does not account for the many factors affecting a purchasing decision that an explicit approach would retain.

A market penetration model should strike a balance between simplicity and accuracy. The desire for increased accuracy usually results in more complex models with a greater number of inputs. For example, many factors work together to cause the costs of new technologies to generally decline over time. This would include the effects of R&D, manufacturing economies-of-scale, and the lessons learned from field applications, to name a few. The analyst must decide which of these factors to address and whether to treat them individually or collectively.

Some of the models investigated use algorithms which allow the analyst to predict market penetration without explicitly considering product characteristics such as cost and performance. For example, defining the shape of a Bass Model s-curve relies heavily on experience with similar products. While this approach is relatively simple, its accuracy relies on the replication of conditions and results experienced with the proxy. Without considerable experience with similar products and stable market conditions, such approaches are likely to be less accurate and probably less defensible than models which explicitly consider product and market characteristics (e.g., initial cost, efficiency, energy prices) affecting market penetration. The latter type of model (represented best by NEMS and the REP Model among the models investigated) is recommended with the implicit judgment that the increase in accuracy is worth more than the cost of increased complexity. The following sections provide a summary comparison of NEMS and the REP Model and a recommended model framework.

4.1 REP Model Versus NEMS

Tables 4.1 and 4.2 summarize the key inputs to the REP Model and NEMS, and the approaches each uses to model technology cost and risk.

The NEMS learning factor performs a similar function to the REP Model's innovation and imitation concept. However, there is a significant difference. The learning factor is a function of cumulative market penetration, while the innovation and imitation factor is driven only by time. Because it is

Table 4.1. Key Inputs to NEMS and REP Model[a]

REP	NEMS
1. Coefficient of Innovation (ρ)	1. Technological Optimism Factor
2. Coefficient of Imitation (q)	2. Learning Factor
3. Initial Risk Premium	3. Leadtime Risk (not currently applied)
4. Logit Function Exponent (λ)	4. Logit Function Exponent(α)
5. Financial Risk (discount rate)	

(a) Not including technology cost and performance characteristics.

Table 4.2. REP Model and NEMS Treatment of Technology Cost and Risk

REP	NEMS
1. Innovation and Imitation (Bass adjustment) - implicitly accounts for all factors lowering a technology's cost and improving its performance over time.	1. Technological Optimism Factor - explicitly accounts for the tendency of technology developers to underestimate cost and overestimate performance.
2. Initial Risk Premium - implicitly accounts for all factors causing a new technology to have a higher cost and perceived level of risk than an n^{th}-of-a-kind technology.	2. Learning Factor - explicitly accounts for the effect of learning on the cost and performance of a new technology as it matures.
3. Financial Risk (discount factor) - explicitly accounts for investment risk issues associated with a particular technology.	3. Leadtime Risk - explicitly accounts for the effect of a technology's leadtime on the financial risk associated with an investment in that technology.

dependent on cumulative market penetration, the learning factor is capable of incorporating the important concept of market lock-in, a common phenomenon affecting technology adoption. For example, the most cost-competitive technology will gain the most market share in year (t), and therefore, the technological optimism and learning factors affecting the technology in year (t+1) will decrease more rapidly than will these same factors affecting the competing technologies. Hence, the most competitive technology's market share grows from year to year while the less competitive technologies lose market share. On the other hand, the NEMS approach does not allow for improvements in technology characteristics accruing through other mechanisms, such as R&D. The REP Model's combination of the initial risk premium and the Bass adjustment performs the same function as does the NEMS' interaction between the technological optimism and learning factor mechanisms.. Both approaches require three estimates, but the NEMS method is slightly more explicit. Finally, both approaches can be constructed to treat financial (leadtime) risk in the same manner.

4.2 Recommended Model Framework

The recommended framework for estimating the market penetration of OEM technologies contains elements drawn from both the REP Model and NEMS. Fundamentally, the framework consists of a market-sharing logit function driven by the life-cycle costs of the competing technologies in any given year. The framework includes several factors for adjusting the life-cycle cost on a year-by-year basis and considers the interactive relationship between a technology's cost, annual market share, and cumulative market share. Various market constraints are also considered.

The framework is outlined below and presented schematically in Figure 4.1. A specific set of equations was not developed because these are expected to vary depending on the technology. For example the "life-cycle cost" measure input to the logit function might be the levelized cost per unit of service or the present value of initial capital and annual operating costs. Market constraints (type and/or amount) will surely be different for different products. The same cost adjustments may not all be applied to all technologies and/or they may have a varying impact. As noted above, different products may warrant varying levels of complexity in an attempt to balance simplicity and accuracy. The central concepts, however, are expected to remain the same.

Market Penetration Model Framework

I. Determine Starting Positions

A. Initial Catalog of Cost and Performance Characteristics for Each of the Competing Technologies (current and mature characteristics for immature technologies)
B. Initial Inventory (Stock) of Each of the Competing Technologies
C. Initial Year Available (for immature technologies)
D. Market Demand Projections for Each Year Throughout the Forecast Horizon

II. Determine Cost Adjustments

A. Immature Technology Risk Premium (function of units installed)
B. R&D "Learning" (function of time)
C. Utilization "Learning" (function of units installed)
D. Production Economies-of-Scale (function of units installed)

III. Calculate the Life-Cycle Cost (LCC) of Each Technology

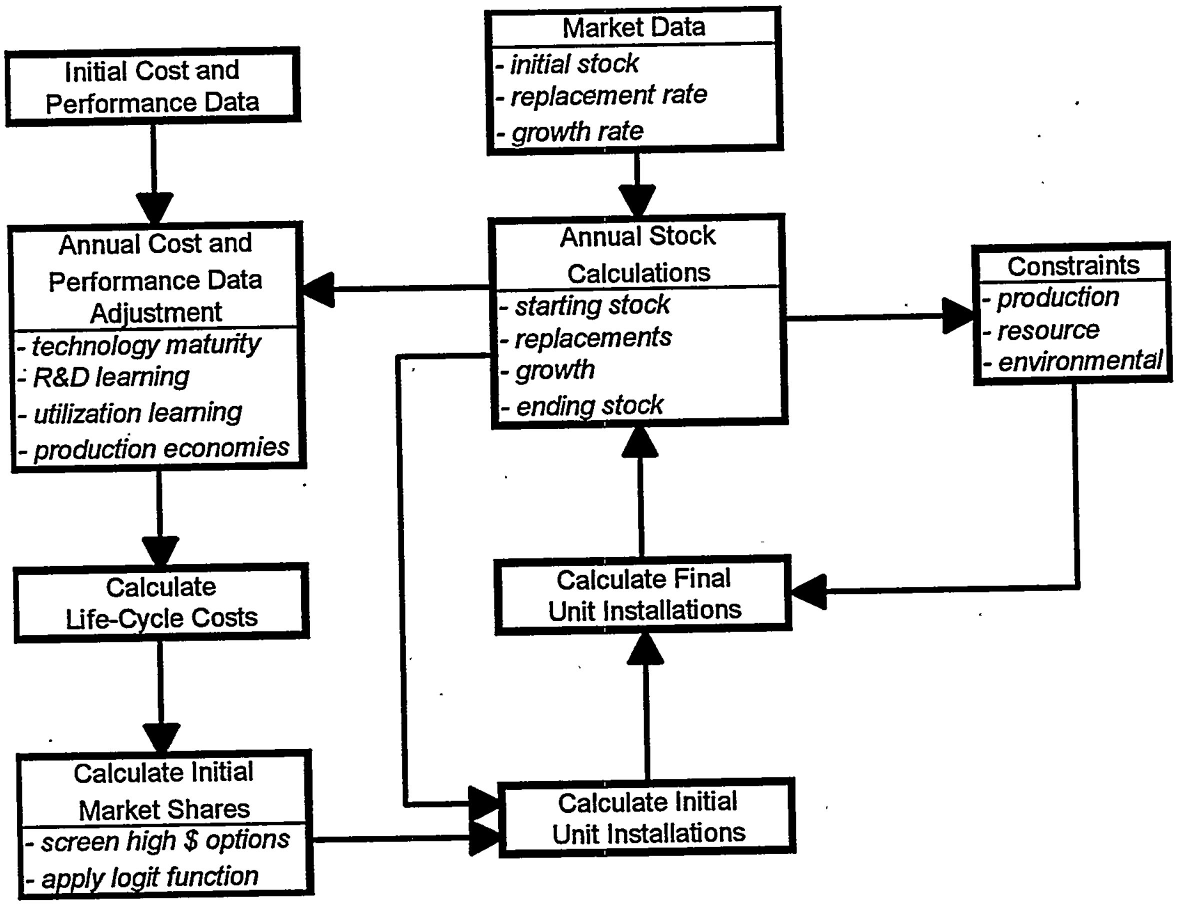

Figure 4.1. Market Penetration Model Framework

IV. Calculate Annual Market Shares

A. Eliminate Non-Competitive Options (LCC too high relative to lowest LCC)
B. Calculate Initial Market Shares (fractions) with Logit Function
C. Calculate Initial Market Shares (capacity)
D. Adjust Market Shares for Technology Capacity Constraints (e.g., production limits, resource limits, environmental limits)

V. Determine Annual Re-Adjustments Resulting from New Market Shares

A. Inventory of Each Technology
B. Technology Cost and Performance
C. Life-Cycle Cost

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