

PRODUCT LIFE CYCLE: A TOOL FOR FORECASTING IN OPERATIONS MANAGEMENT

by

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ABSTRACT

The production operations managers have been concerned about new product development and the life cycle of these products. Because many products do not sell at constant levels throughout their lives, product life cycles must be considered when developing sales forecasts. Wide variations in the amount of time different products take to pass through a given life cycle phase exist. Some products pass through the entire life cycle in a relatively short period of time, other products take considerably longer. How long it takes a product to pass through its life cycle is related to the basic need for the good and the rate of adoption or diffusion into the marketplace. Innovation diffusion models have successfully been employed to investigate the rate at which goods and/or services pass through the product life cycle. This research investigates innovation diffusion models and their relation to the product life cycle. A novel extension to the original Mansfield innovation diffusion model is proposed. The model is developed and then tested using modem sales from 2003-2012. Each successive generation of modem innovation, from 14.4k, 28.8k, 56k, to broadband, is examined.

KEYWORDS: Product Life Cycle, Innovation diffusion models, Logistic growth model, parameter, forecasts

INTRODUCTION

Generation of new product opportunities has been a major area of study in production and operations management for decades. Products are born, they live, and then many die and many stay for long in the market. They are cast aside by a changing society as consumer's needs and wants change. Production operations managers are an integral part this cycle. This cycle is generally referred to as the Product Life Cycle (PLC). Examination of products as they move through their life cycle is crucial to a firm's success. Production operations managers are challenged with developing new strategies, examining ongoing strategies, and eliminating non-competitive strategies for a product's diffusion into markets. Many times it is the primary job of the operations and marketing managers to forecast a product's diffusion. Within the operations discipline the product life cycle and forecasting can be linked using what is called innovation diffusion theory.

BACKGROUND AND LITERATURE REVIEW

Innovation diffusion theory has received considerable attention since its inception in the 1960's. The diffusion of innovation can be defined as the process by which an innovation is imparted on members of society through certain channels over time (Rogers 1983). Seminal works in the area of technological change and rates of imitation were completed by Fout and Woodlock (1960) and Mansfield (1961). The work by Fout and Woodlock (1960) and Mansfield (1961) are the basis for research in diffusion modelling by Bass (1969).

Research in the area of innovation diffusion has been accomplished by academics in many fields including marketing management, consumer behaviour, and production operations management. The Bass model for new product growth and innovation diffusion has been used to forecast numerous products in many different industries.

Mahajan and Muller (1979) and Mahajan, Muller, and Bass (1990) provide a review of the contributions to this literature through the 1970's and on into the 1980's. Young (1993) provides an excellent article comparing nine growth and innovation diffusion models including Mansfield's and Bass' models. Grover et al. (1998) and Harrison et al. (1997) discuss the influence of information technology diffusion on large and small businesses. This work proposes a novel extension to the original Mansfield model applied to the technology industry. The model is developed and then tested using modem sales from 2003-2012. The model is applied to each successive generation of modem innovation: 14.4k, 28.8k, 56k, and broadband.

NEW PRODUCT GROWTH AND INNOVATION DIFFUSION MODELS

A number of different new product growth and innovation diffusion models exist. These models differ in their underlying mathematical characteristics and assumptions. Some of the main differences include using cumulative sales levels versus the sales growth rate of change and the underlying functional form of the diffusion curve. The logistic growth model is cornerstone to many of these models. The logistic growth model can be described by the following equation:

$$Y_t = \frac{L}{1 + ae^{-(bt)}}$$

where Y_t is the cumulative level of sales at a given time, t , L is a measure of the upper limit of market sales or the total market capacity, and a and b are parameters that define how quickly a product diffuses into a market. Specifically, a defines how dispersed the product life cycle is or the product's position in its life cycle, whereas, b describes how peaked the product's life cycle or what the rate of change over time is of the product's diffusion into the market. Larger values of a characterize products in the early phases of their product life cycles and larger values of b characterize more peaked life cycles and faster rates of change over time. These parameters, a and b , must be estimated.

This model is very similar to Mansfield’s original model which is described by the following equation:

$$Y_t = \frac{1}{1 + e^{-(a+bt)}}$$

However, in comparing the logistic model with Mansfield’s, two differences exist. First, Mansfield does not specify an upper limit on market sales, L. On the surface this appears to be a major difference, however, by not specifying an upper limit of market sales Mansfield’s model speaks to percentage diffusion and not total unit diffusion. Second, Mansfield’s model functionally employs the a and b parameters in a different manner. Instead of using a to modify the output from the exponential calculation, Mansfield uses a in a linear combination with b.

This allows Mansfield’s model to be represented as a linear version of the logistic model. Although Mansfield’s model can be estimated using linear regression there are drawbacks including the validity of the linear regression variance assumption and the concern that L, the upper market limit, must be known to perform complete analysis. For these reasons, this work chooses to employ the logistic growth model as the underlying functional form.

CUMULATIVE NATURE OF THE LOGISTIC GROWTH MODEL

The underlying logistic growth model is cumulative in nature. Y_t is defined as the absolute or cumulative level of diffusion at time t. Figure 1 displays the analytical structure underlying the logistic growth model in its cumulative form, Y_t .

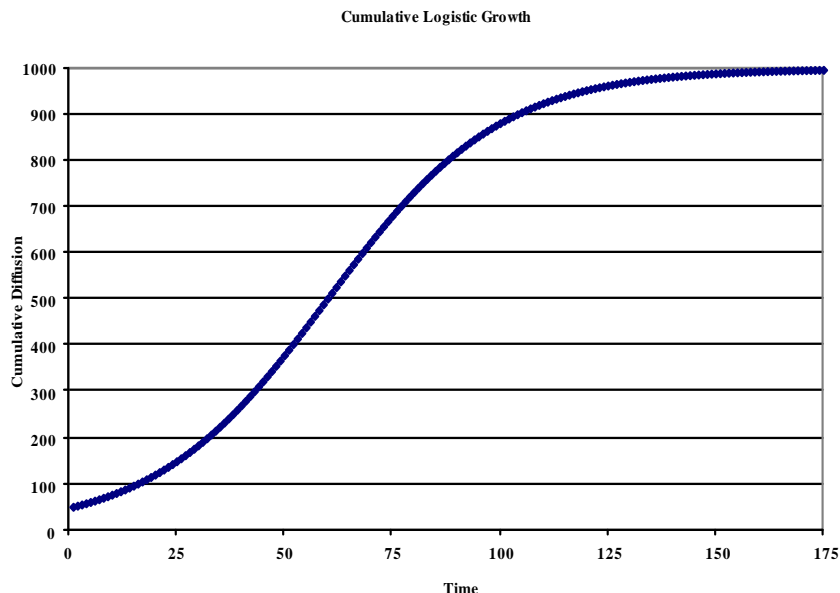


Figure 1 Cumulative Logistic Growth Curve

The cumulative nature of diffusion is captured in the above figure. It can be seen that the logistic curve in its cumulative form takes on an S-shape. This is common to many diffusion models. However, many production and operation managers without formal

training in logistic forecasting models would be unable to derive critical information from this function such as: time to peak sales, sales at future time t , overall shape of the diffusion curve etc. Additionally, if data such as per period sales numbers were being collected, the cumulative nature of the S-shaped function does not lend itself to easy interpretation or forecasting. Therefore, this paper proposes a novel approach in analyzing the logistic growth diffusion model.

In order to portray the data in a manner that most production and operation managers can identify with, the research proposes taking a first derivative of Y_t to obtain the non-cumulative form of the logistic growth diffusion model. In doing so, critical information that production and operation managers seek are: peak time to sales, sales at future time t , and the overall shape of the diffusion curve which will become more apparent. The non-cumulative form (i.e., first derivative) of the logistic growth diffusion model is as follows:

$$y_t = \frac{abLe^{-(bt)}}{(1 + ae^{-(bt)})^2}$$

Figure 2 displays the analytical structure underlying the logistic growth model in its non-cumulative form, y_t .

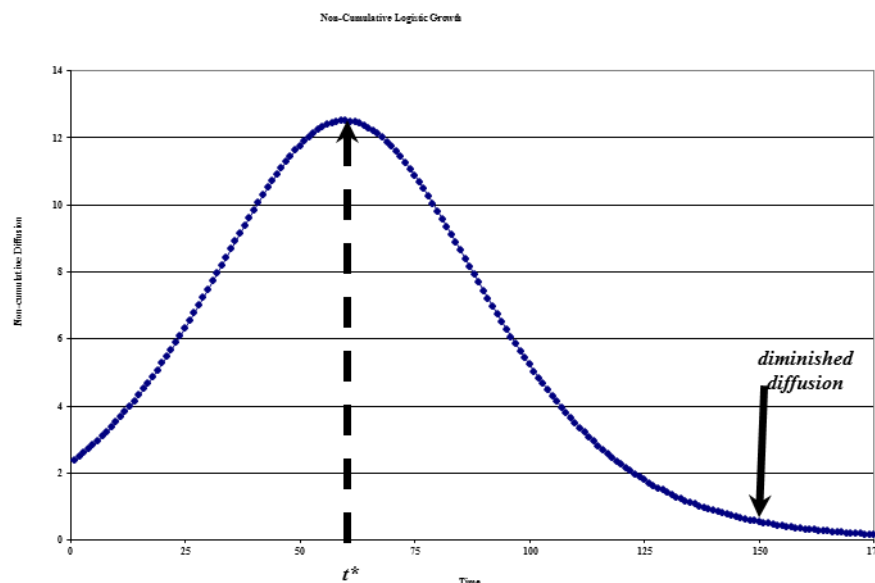


Fig. 2 Non-Cumulative Logistic Growth Curve

It can be seen that the logistic curve in its non-cumulative form takes on a bell shape and is symmetrical. With this representation it is clear at what time peak diffusion occurs, where sales at future time t occur, and what the overall shape of the diffusion curve is. For example, the dotted arrow in Figure 2 depicts the approximate time of peak diffusion, t^* , as approximately 60. It is also easy to observe that diffusion really diminishes after time period $t = 150$. Diminished diffusion is represented by the bold arrow in Figure 2 and characterized as the time when diffusion falls below a pre-defined market sales level.

The non-cumulative form of the logistic growth diffusion model lends itself to operations managers as more user-friendly source for critical information. In addition, if a manager is collecting time series data on sales, that data will be presented in a period-by-period non-cumulative manner. Therefore, using the non-cumulative logistic diffusion model to build a sales forecast is inherently more obvious.

APPLICATION OF LOGISTIC GROWTH DIFFUSION MODEL

Numerous studies have been conducted on various products using diffusion innovation models. The original Mansfield model has been used to forecast industrial products, high technology products, and administrative innovations (Mahajan, et al., 1990). Since the original Mansfield model relies on an underlying logistic diffusion model, a logical extension was made that the non-cumulative logistic diffusion model would also be highly useful in forecasting technological product innovation.

METHODOLOGY

To perform the experimentation required to test the non-cumulative logistic diffusion model, data sets were gathered. The data sets consisted of modem equipment percentage penetration for 14.4k, 28.8/33.6k, 56k, and broadband modems from 2003 to 2012. The data was compiled using The Bandwidth Report. All data sets were categorized as non-cumulative and in percentage penetration values. One data set was also defined by an unknown upper limit.

For each data set a non-linear estimation procedure was employed to estimate the parameters of interest. This was accomplished via Excel and Solver. The model fit of each non-linear estimation procedure was reported by mean absolute error (MAD). Forecasts were made via each model for one-step-ahead time periods. Peak diffusion locations and periods of diminishing diffusion were also investigated. These results are presented in the next section.

RESULTS

The non-cumulative logistic diffusion model requires the estimation of three parameters, a, b, and L. Table 1 contains the parameter estimates using the modem data resulting from the non-linear regression procedure. All parameter estimates are positive and they are all plausible. The parameter b estimates are discussed first as they are considered to be the most interesting (Bass, 1961; Norton and Bass, 1986) followed by discussion of the parameters a and L.

PARAMETER B ESTIMATES

Norton and Bass (1986) discuss the magnitude of the parameter estimate for b. They comment that for a given technology class, the behavioral process for adoption of advancing generations could be expected to be similar. It is seen from Table 1 that the magnitude of b is on average 0.052 within a range of ± 0.005 .

This not only adds validity to Norton and Bass’ claim, it is very interesting since the estimates of b were made independently of each other (i.e., four separate non-linear regression procedures).

Parameter	14.4k	28.8k	56k	Broadband
L	48.0	47.2	49.9	41
A	0.895	9.0	92	740
B	0.048	0.057	0.051	0.050
R ²	0.988	0.970	0.957	0.994

Table 1 Parameter Estimates for Non-cumulative Logistic Function

PARAMETER A ESTIMATES

Investigating the parameter a also leads to some interesting conclusions. The parameter a characterizes how disperse the product life cycle is or the product’s position in its life cycle. Larger values of a characterize products in the early phases of their product life cycles. Over the past decade, the progression of modem technology has been as follows from earliest to latest: 14.4k, 28.8k, 56k, and Broadband. The values for a logically follow this progression. From Table 1, it can be noted that estimates of a increase from 0.895 for 14.4k modems (earliest technology) to 740 for Broadband (latest technology). In other words, the 14.4k modem technology is late in its product life cycle whereas the Broadband technology is early in its product life cycle.

PARAMETER L ESTIMATES

The estimates for the parameter L range between 41 and 50. L is described as a measure of upper market sales level. The estimates appear to be explaining that the overall market for any modem technology, no matter what generation it falls in, has an upper limit on market sales or in this case penetration. The parameter estimates of L in Table 1 validate the underlying concept of the product life cycle and the introduction of successive, newer generations of modem technology into the market. As successive generations of newer technology are being introduced penetration of older technology that at one time dominated the marketplace, must peak and then decline. The estimates show that for any of the modem technologies introduced in this example an almost constant upper limit of market penetration appears.

MODEL FIT STATISTICS

Table 1 also displays the fit of the model to the data for Modems. The R² values are all high, the lowest being greater than 0.95. The degree of R² for each model augments the Norton and Bass’ (1986) belief that the rate of adoption should be similar for advancing generations of similar technology. Figure 3 displays the fit of the model to the data in

graphical form. It is very apparent from Figure 3 that there exists a close association between the model and the actual data.

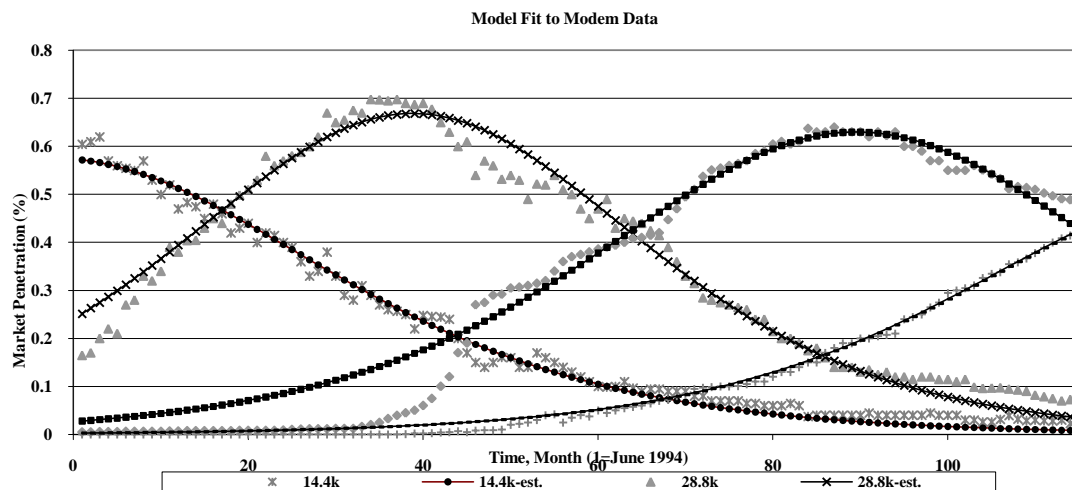


Fig. 3 Model Fit to Modem Data

FORECASTS

The principal use of the non-cumulative diffusion growth model is for production and operation managers to make more detailed and accurate forecasts of new products and successive technology. Therefore, forecasts are made via each model for one-step-ahead time periods, peak diffusion locations, and periods of diminishing diffusion are also investigated. Table 2 displays the one-step-ahead forecasts for each modem technology.

Results	14.4k	28.8k	56k	Broadband
Forecast				
1-step-ahead	0.008	0.033	0.415	0.434
Peak Location				
Time, t	-2	39	89-90	132-133
Date	March'03	August'06	October'09	June'12
Diffusion %	57.6%	66.9%	63%	51.1%
Diminishing Diffusion:				
Time, t	80	110	170	210
Date	January'03	July'06	August'09	January'12

Table 2 Non-cumulative Diffusion Growth Model Forecasts

The one-step-ahead forecasts in Table 2 depict the near future of modem technology market penetration. Broadband and 56k modems make up the bulk of the market, 84.9% of the market, with 28.8k modems making up just 3.3% and 14.4k modems almost completely pushed out by the newer technology. The forecasted numbers do not add up to exactly 100% due to rounding error and the expectation of a newer technology being introduced into the market that was not measured by this research.

Peak diffusion locations are listed in Table 2 by time, t , date, and diffusion percentage. The time, t , to peak diffusion varies slightly from successive generation to successive generation. For example, peak to peak diffusion time between 14.4k and 28.8k modems and peak to peak diffusion time between 56k and Broadband modems are relatively constant, 41 and 43 months respectively. These peak to peak diffusion times differ from the peak to peak diffusion time for 28.8k and 56k modems which is 53 months. This is most likely attributable to the long debates surrounding the adoption of a 56k modem standard in the high-tech industry.

For operations managers, the most interesting numbers from Table 2 are the peak diffusion location for broadband modems and the diminishing diffusion points for 56k and broadband modems. The Production and Operation managers would be interested in these estimates due to their relevance to new product design cycles and production planning. The peak diffusion location for broadband modems is estimated to be around time period, $t = 132-133$. It could be expected that broadband modems will penetrate around 51.1% of the market share before another newer technology begins to substitute.

The diminishing diffusion point characterizes the point where a technology market share falls below the 5% penetration level. In other words, diminishing diffusion occurs when the technology has almost wholly been substituted for by other newer technologies. For 56k modems the diminishing diffusion point is approximately time period, $t = 170$. This prediction does have a logical basis in that at least a portion of future Internet users will still live in areas not served by broadband providers. Broadband modems can expect to reach a diminishing diffusion point at time period, $t = 210$ or January of 2012. Although broadband modems are the latest generation of technology, newer technologies are on the horizon. The diffusion model predicts that a newer generation of technology will begin to make inroads into the high speed Internet delivery market in the coming years.

The Production and Operation managers have long sought a method to assist in forecasting the demand for new products and diffusion of successive generations of products into the market. The model appears to help in illustrating peak market diffusion points and points of diminishing diffusion. It must be noted that additional studies must be conducted using the underlying model for various product types before these findings can be completely generalized.

CONCLUSION

The life of most products travel through a birth-death cycle referred to as the Product Life Cycle. The Production Operation managers are an integral part of this cycle. Examination of products as they move through their life cycle, or diffuse, is crucial to a firm's success.

This work researches the rate of diffusion for one product's life cycle. The Production Operation managers are challenged with understanding the impact, a new product will have on the market. Many times a product's diffusion into a market is directly linked to forecasting. The unique contribution of this work to the area of production operations is linking the concepts of product life cycle and forecasting using Innovation Diffusion theory.

The purpose of this paper has been to present and test a simple, yet novel model designed to investigate the differences or similarities between successive generations of a high technology product, namely the modem. The underlying model is based on the assumption that the percentage of market penetration at any time is related linearly to the previous market penetration.

Data for modem market penetration are in very good agreement with the underlying modified Mansfield model. Parameter estimates derived from non-linear regression analysis when used in concert with the model provide accurate descriptions of modem market penetration for successive product generations. For the Production Operation managers the interest in innovation diffusion models lies in the predictions of the timing and magnitude of the market penetration peak. As was described in the results section, the model provides good estimates of both timing and magnitude of the modem market penetration peak. For the production and operation managers, the model appears very useful as a vehicle to provide a long-range planning rationale for forecasting the diffusion of successive generations of new products.

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