*Sonja Radas**

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FORECASTING THE LIFE CYCLE OF A NEW SEASONAL DURABLE

Autorica je u članku ponudila novu verziju Bassovog modela u koju je ukomponirana sezonalnost. Time je značajno ubrzan proces primjene modela, i taj je novi model primijenila na konkretnim podacima jedne američke tvrtke. Razvitak novog proizvoda je izuzetno važan za opstanak svake tvrtke. Zbog velikog rizika vezanoga uz inovacije, u praksi se koriste dobro osmišljeni programi razvitka tvrtke.

Introduction

Most companies recognize that a continuing stream of new product developments is essential to ensure long-term organizational health. But they also recognize that innovation is accompanied by high costs and risks. These risks can be controlled through a well-conceived and professionally managed program of new product development. In new product launch situations, the assessment of sales that can be expected over a future planning horizon and the diagnosis of difficulties with the product, its distribution and promotion are critical.

One of the key ingredients of such a new product development program is the use of explicit models for planning and forecasting sales (Urban and Hauser 1993, Crawford 1994, Dolan 1993). One class of such models is diffusion models. The task of a diffusion model is to produce a life-cycle sales curve based on a small number of parameters. The most popular diffusion model used in marketing is Bass diffusion model (Bass 1969, Bass Krishnan and Jain 1994). This model is used for forecasting the long-term sales pattern of new technologies and new durable products when the firm has recently introduced the product or technology and has observed its sales for a few time periods. It can be also employed to develop a

* S. Radas, Assistant Professor of Marketing, Olin School of Business, Washington University in St. Louis, USA. Članak primljen u uredništvu: 10. 01. 2001.

forecast on the basis of life cycles of analogue products before the product is introduced. The model attempts to predict how many customers adopt the new product and when they will adopt. The question of "when" is important, because the answers will guide firm in its deployment of resources in marketing the innovation.

Most firms work continuously on enhancing their new products, which are then marketed as "new generation" products. Knowing the life cycle of the product makes it possible to decide when to introduce a new and improved version. This is usually done before sales enter the saturation phase. Forecasting the life cycle gives the firm the needed information about when the product is expected to enter this phase.

The Bass model, as other diffusion models, does not account for seasonal variations in sales. One way to remove seasonality from data is to use yearly data, as has been done often in the past. However, the increasing global competition and resulting shortening of product life cycles do not allow managers to wait for several years before they attempt to forecast the life cycle. Crucial decisions have to be made very soon after the product's launch, so models that require several months of data vs. several years of data would be very useful. Such models should account for seasonal variations in sales predictions. One method for incorporating seasonality in any dynamic model is introduced in Radas and Shugan 1998 (for better readability from now on this method is referred to as RS-method). This method applied to Bass diffusion model allows forecasting from just several months of data. Using this method, managers can react faster to possible problems indicated by the long-term forecast through adjusting the marketing mix variables accordingly.

In this paper the author shows how applying the RS-method to the Bass model yields long-term sales forecast of a seasonal product based on only one year of data. The model is applied to life cycle forecasting of an air filter for woodworking shops, which is produced by an American company specialized in air systems. Among the purposes of the particular forecasting project described in this paper is to find the best time for introduction of an improved version of the filter.

Modeling seasonality

Seasonal changes affect sales of most products and services. Seasonality, like the economy, is a feature of the firm's external environment. It can be caused by weather, industry traditions, government actions etc. Most products and services are seasonal.

Firms usually know the seasonal pattern of their industry. They use this information to plan product development, launch and post-launch activities. A popular example of a highly seasonal industry is US motion picture industry.[1] Other firms in other industries also consider seasonality when making their decisions on when and how to launch their new products.

Here follows a short description of the RS-method (for more detailed description see Radas and Shugan 1998). The method views seasonality as changes in the rate at which transactions occur. During high seasons, more transactions occur per unit time. Time moves faster, so more purchases occur and the product moves more quickly through its life cycle. During off-seasons, time slows down, some buyers may stop buying, and the product moves more slowly through its life cycle.

The method requires that the firm knows its seasonal pattern. Known seasonality pattern is defined as the function $g(t)$. This $g(t)$ provides valuable input for strategic decisions. It can be measured in any units including attendance, unit sales or dollar sales. By $f(t)$ we define transformed time, abbreviated $T=f(t)$. This function accelerates time during high seasons. The duration of a seasonal cycle, in transformed time, equals the duration in normal time. Hence, after each cycle, transformed and normal time must equate. Equation (1) defines transformed time accordingly. Here, N is the number of periods in the seasonal cycle, and K is a constant.

$$T = f(t) = K\int_0^t g(u)\,du \quad \text{where } K = \frac{N}{\int_0^N g(u)\,du} \tag{1}$$

We now define the following notation where $S(t)$ is <u>any</u> dynamic model of sales over time. Let:

$Y(t)$ = Cumulative sales to normal time t.

$S(t)$ = Sales in normal time, by definition, $S(t) = dY(t)/dt$.

$Y_T(t)$ = Cumulative sales to transformed time T

$S_T(t)$ = Sales in transformed time, by definition, $S_T(T) = dY_T(T)/dT$

m = The ultimate market size, where: $m = \lim_{t \to \infty} Y(t)$

[1] Seasonality has a huge impact on all the studio's decisions about production and release of films. Studios have a projected release date even before the shooting starts. This planned date is usually not the actual release date, but in most cases the difference between the two is only several weeks or so. The film production is planned in anticipation of this desired release date. When the release date is publicly announced, then the signaling game begins. Other studios adjust their release dates if they think they have a weaker product, or they stay put if they are confident. During the high season (summer months and Christmas) market is so cluttered by new films that this competitive signaling gets very intense. Studios fight for good release dates months before the season starts.

Note, cumulative sales in normal time always equals cumulative sales in transformed time, because $Y(t)=Y(f^{-1}(f(t)))=Y(f^{-1}(T))=Y_T(T)$. Hence, $Y(t)=Y_T(T)$ everywhere. Moreover, $S(t) = dY(t)/dt$, therefore $S(t) = S_T(f(t)) \cdot f'(t)$. We now use $f(t)$ to deseasonalize sales. See Equation (2).

$$S_T\left(f(t)\right)=\frac{S(t)}{f'(t)} \tag{2}$$

Although $S(t)$ is continuous, data are discrete. As a discrete approximation, let $f'(t) = f(t)-f(t-1)$. So, $s_T(T) = s(t)/[f(t)-f(t-1)]$, where $s(t)$ and $s_T(T)$ are discrete sales in normal and transformed time, respectively.

Bass Diffusio Model

Suppose that the cumulative probability that someone in the target segment will adopt the innovation by time t is given by a non-decreasing continuous function $F(t)$, where $F(t)$ approaches 1 (certain adoption) as t gets large. The derivative of $F(t)$ is the probability function $f(t)$. This function indicates the rate at which the probability of adoption is changing at time t. To estimate $F(t)$ we can specify the conditional likelihood $L(t)$ that a customer will adapt the innovation at exactly time t since introduction, given that the consumer has not adopted before that time. Using the Bayes rule, we can write this likelihood as

$$L(t)=\frac{f(t)}{1-F(t)} \tag{3}$$

Bass (1969) proposed that L(t) be defined as

$$L(t)=p+\frac{q}{m}Y(t) \tag{4}$$

where

$Y(t)$ = the number of customer who have already adopted by time t (i.e. cumulative sales to time t)

m= total market size (all customers who will eventually adopt the product)

p = coefficient of innovation (or coefficient of internal influence)

q= coefficient of imitation (or coefficient of external influence).

We can interpret equation (4) in the following way: the likelihood that a customer in the target market will adopt at time t is the sum of two components. The first component p refers to a constant propensity to adopt. This tendency is independent of how many people have already adopted the product before time t. The second component $(q/m)\cdot Y(t)$ is proportional to the number of customers who have already adopted. It represents the social "pressure" to adopt the innovation, which stems from increased number of adopters in the market. Coefficient p is usually linked with advertising and customer awareness, while q is generally connected with word-of-mouth, product quality and customer satisfaction.

From (3) and (4) we can express the density function as

$$f(t)=\left[p+\frac{q}{m}Y(t)\right]\left[1-F(t)\right] \tag{5}$$

Since the number of adopters by time t can be expressed as $Y(t) = m\cdot F(t)$, we can get the following equation for predicting the number adopters of the product at exactly time t. We usually refer to this number as "sales at t", and denote it by $S(t)$.

$$S(t)= pm+ (q-p)Y(t)-\frac{q}{m}\left[Y(t)\right]^2 \tag{6}$$

In order to use discrete sales data this formula is transformed to

$$s(t)= pm+ (q-p)y(t)-\frac{q}{m}\left[y(t)\right]^2 \tag{7}$$

where $s(t)$ represents discrete sales in time t, and $y(t)$ stands for cumulative sales up to time t but not including time t. We estimate parameters p, q and m using least-squares regression.

Forecasting the life Cycle of an air Filter

Product life cycle is an important concept which underlies most dynamic business planning models. By using the life cycle firms can anticipate how sales might evolve, and they can develop strategies to influence those sales. For example, the firm can use life cycle to plan advertising support, simulate impact of competitor's actions, make decision on when to introduce a new generation of existing product, etc. In this paper it is demonstrated how the RS-method and Bass model can be used to predict the life cycle of a new seasonal durable. This method is applied to forecasting long-term sales of an air filter.

Aurora Air Systems, Inc.[2] is a company based in the USA. The company produces air systems for woodworking shops. Several years ago Aurora's engineers invented a new technology that allowed them to design an air filter that was much better than any other filter available on the market. The new product had an advantage that it was able to collect many more microscopically fine dust particles and retain them in the filter, rather than spill them partially out again as competitive products did. The filter was targeted to small woodworking shops as well as hobbyists. Initial sales showed that Aurora had a winner product in their hands. The filter was so popular that a big competitor started copying it. Aurora expected the competitor to launch its product about 12 months after Aurora's filter was introduced. The competitor was a large and established company producing mostly woodworking tools and enjoying good brand name and recognition. Aurora believed that the competitor did not master the technology well enough to make a good copy of Aurora's filter, however the competitor was expected to take a considerable chunk of the market because of its brand name and its ability to engage in heavy advertising. It also had an advantage of having distribution channels already in place, while Aurora was just setting these up. To counteract competition, Aurora had an improved technology ready for introduction of a new and enhanced filter. To find the best time for new filter's introduction, Aurora needed the forecast of the parent filter's life cycle.[3]

Air filters for woodworking industry are very seasonal products. Low season is in summer, while high season is in winter. This particular pattern is partly influenced by weather; namely it is possible to open windows in summer for shop ventilation, while in winter most people must resort to air filters. In order to predict future sales from the least amount of data (less than 1 year) one needs to incorporate seasonality in forecasting. Such a forecast incorporates all the seasonal ups and downs. In order to develop such a forecast, the author applied the RS-method to the Bass model.

The first step in RS-method is to find the seasonal pattern for air filters in woodworking industry. The data used included government industry publications and Aurora's total sales of their other products (all of them air systems) in the previous 5 years. Since the company was growing and adding more products, the author adjusted these sales for the sales trend. On the adjusted data the author performed OLS regression with seasonal dummies (adjusted R^2= 70%). This result is checked against industry publications to see if the resulting seasonal pattern conforms to the data found there. The resulting seasonal pattern is shown in the figure 1.[4]

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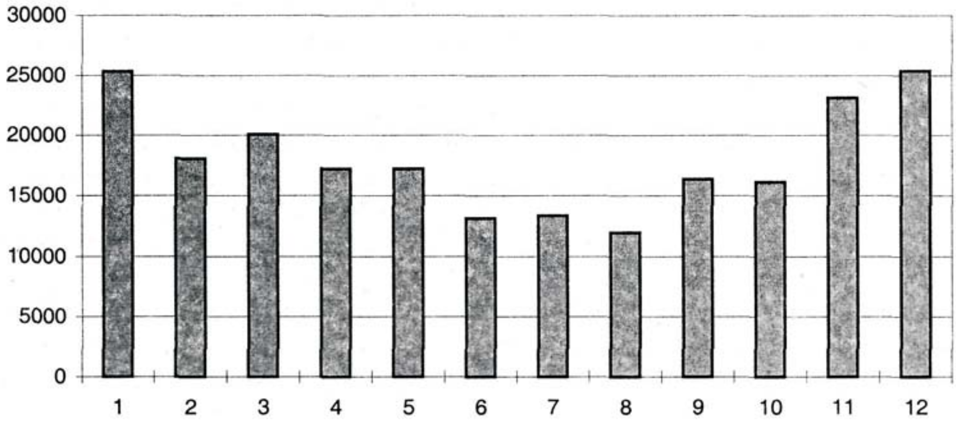
[2] The name is changed to preserve confidentiality.

[3] All the numbers in this paper are transformed using a linear function at the company's request.

[4] This seasonal pattern is expressed in US dollars because the underlying data was sales. However, this does not impact the further calculations because of the way $f(t)$ is defined (see formula (1)).

Figure 1

SEASONALITY PATTERN



Aurora determined the ultimate market size on the bases of their managerial knowledge of their target market. They also used access to trade lists and magazine circulations (for example Fine Woodworking) targeted to small woodworking shops and hobbyists. In the end, they came up with the total market size approximation of about 4500 buyers (this translates into about 1.5 million US dollars). This number is based on the assumption that the firm will not alter its marketing mix, nor will anything drastic happen on the market (for example the competitive situation is assumed constant).[5] We can also address the various competitive and market scenarios by adapting this method somewhat, as will be shown in the remainder of this paper.

The author first deseasonalized air filter's available sales (11 months) by using the seasonal pattern in figure 1 and formula $s_T(T) = s(t)/[f(t)\text{-}f(t\text{-}1)]$. Bass model is applied to these deseasionalized sales[6] (see formula (7)). After that the resulting curve is seasonally adjusted by applying formula $s(t) = s_T(T)/[f(t)\text{-}f(t\text{-}1)]$.

The ensuing ultimate market size estimate from this assessment is 4019 users, which is close to Aurora's projection. Estimate of coefficient of innovation is p=0.006, which is very small. This reflects Aurora's lack of advertising resources. Aurora advertised only infrequently in a limited number of woodworking

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[5] In other words, the firm has to answer this question: " if everything remains the same as today, what do you think is your ultimate market size?"

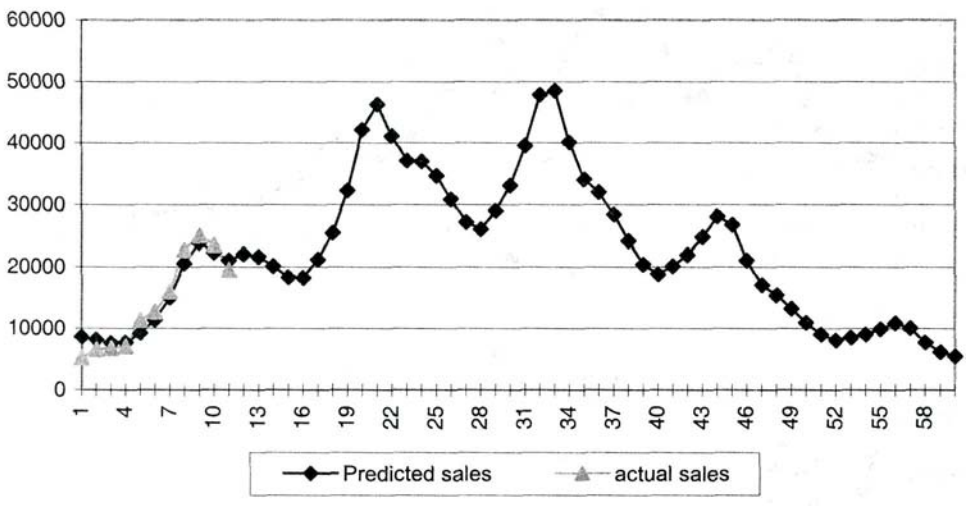
[6] These are also referred to as sales in transformed time.

publications due to lack of funds. Their CEO recognized the need for raising awareness through use of other methods, but their financial situation did not allow for an increase in advertising spending. Aurora filter's main source of advertising was excellent word of mouth from a small number of very satisfied current users. The main coefficient of imitation was estimated to be q=0.09. Altogether relatively large i.e. more than ten times larger than p, this q is still small, which suggests a very slow diffusion pattern. This is most likely due to the fact that woodworking shops do not come in contact often, and do so only on special occasions like fairs, trade shows etc. This inhibits word-of-mouth.

Using estimated diffusion parameters, we can forecast the long-term dollar sales of Aurora's air filter, as shown in the figure 2.

Figure 2

LIFE CYCLE OF AURORA'S AIR FILTER



Ups and downs in the above graph come from seasonal changes. This graph shows the importance of forecasting using seasonal models; namely without seasonal forecasting a seasonal downturn can be wrongly interpreted as a permanent decline in sales. The forecast reveals that, if everything remains the same (Aurora's marketing mix, market conditions, etc.), Aurora can expect the filter sales to reach their peak 33 months after introduction. This means that the new and improved version should be launched about or a little after this time.

It is important to point out again that this forecast is obtained under assumption of no change in the market and the firm. The information that this forecast yields is certainly useful, but even more valuable is the possibility to model various competitive and other scenarios. This will be illustrated in the remainder of his paper.

Aurora did not have sufficient funds to engage in more aggressive advertising, at least not so much that we could expect a significant impact on p in the next couple of years. Just to illustrate how raising p impacts diffusion, we will look at two imaginary scenarios shown in figure 3 and 4.

Figure 3

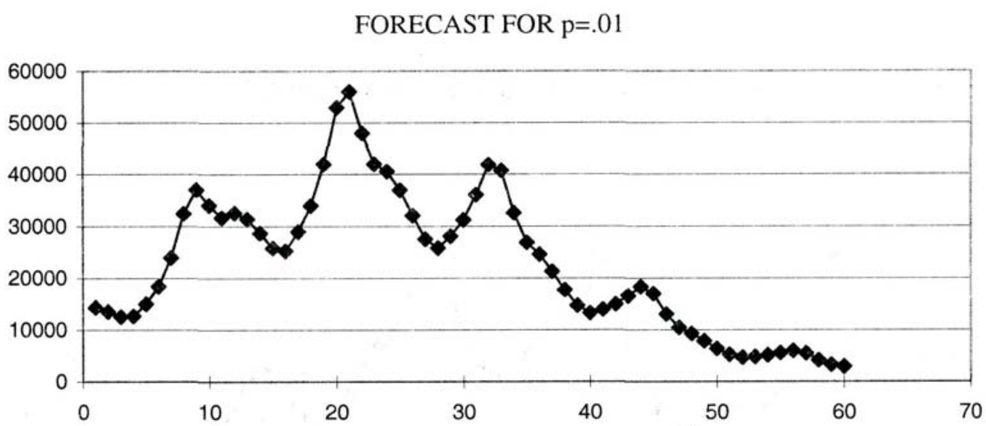
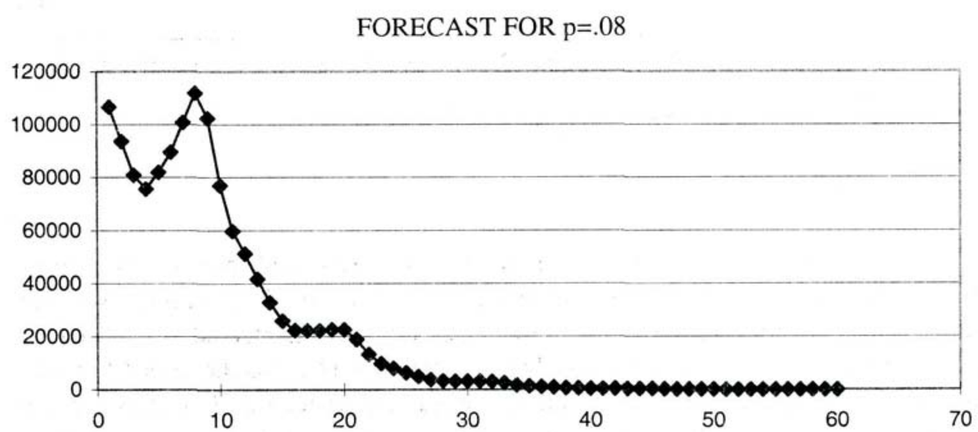


Figure 4



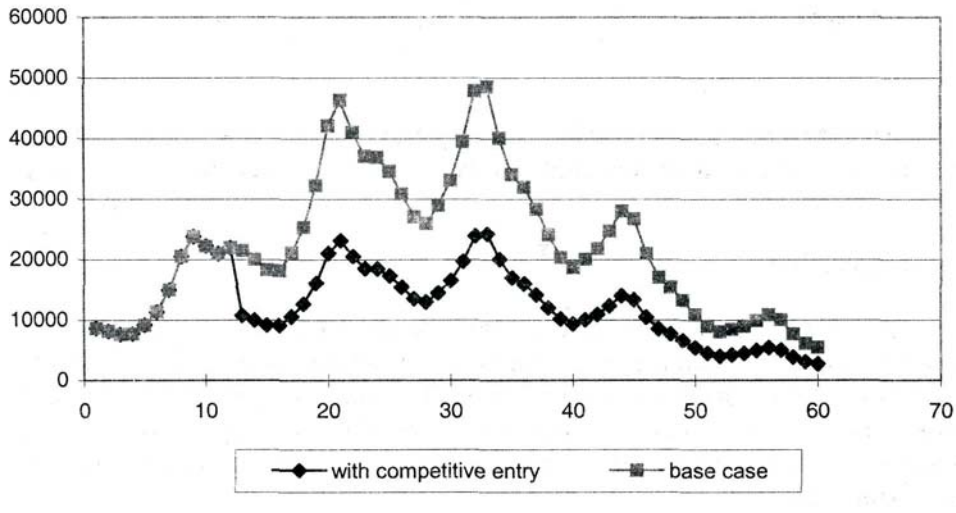
It is obvious that raising *p* speeds up the diffusion process. Consequently the market is exhausted sooner. This is helpful in fighting competitive encroachments, but requires financial strength to support adequate advertising. If Aurora had sufficient funds to substantially raise *p* to 0.08, it would have harvested majority of sales before the year was up. One has to proceed with caution here, because the price of raising *p* to such level might have been so high as to offset the benefits of fast diffusion.

Aurora was very interested in examining various competitive scenarios. It feared competitive action from an established player about a year after the launch of its own filter. Presented below are some competitive scenarios and corresponding life cycle forecasts. The exact competitive scenarios (how many competitors, impact on market size etc.) are provided by the firm's management.

Figure 5 demonstrates the competitive impact on filter's sales based on assumption that the competitor enters one year after the filter's introduction and takes 50% of the market.

Figure 5

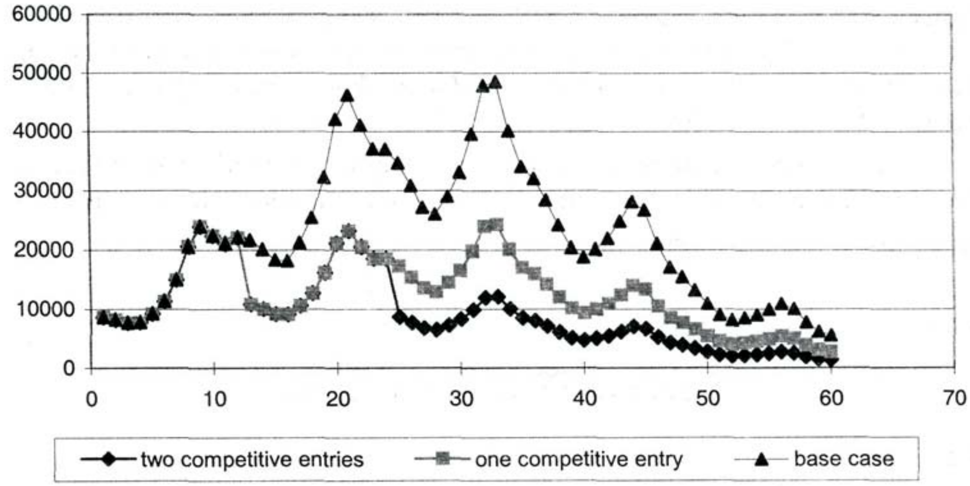
EFFECT OF A COMPETITIVE ENTRY



Again sales peak at 33 months after the launch, so the timing of new and improved filter introduction does not have to be changed drastically because of competitor's action. If another competitor would enter at year 2, then this new timing would change because the peak sales happen earlier (at 21 months), as demonstrated in the following figure 6. We assume that the new competitor would again take 50% percent of the remaining market, which then leaves Aurora with 25% of initial total market size.

Figure 6

EFFECT OF TWO COMPETITIVE ENTRYES



In reality much greater number of competitive scenarios were examined. All this analysis helped Aurora to decide on their marketing and competitive actions.

Conclusion

A continuing stream of new product developments is essential to ensure long-term organizational health. As innovation is accompanied by high costs and risks, using a well-conceived and professionally managed program of new product development is crucial in controlling risks. One of the key ingredients of a new product development program is the use of explicit models for planning and forecasting sales.

In marketing there is a long tradition of the use of diffusion models to forecast long-term sales of a new durable or technology. The task of a diffusion model is to produce a life-cycle sales curve based on a small number of parameters. Among other things, the firm uses this forecast to adjust marketing mix variables, anticipate competitive moves, and plan introductions of new products and technologies.

Up to 1998 diffusion models did not incorporate seasonality. Diffusion model forecasting either had to disregard seasonal changes and risk inaccurate results, or had to resort to using sales from full seasonal cycles (for example yearly data). This can be circumvented by explicitly modeling seasonal fluctuations. Explicitly incorporating seasonality in forecasting is important because it makes it possible for managers to obtain their forecast sooner (there is no need to wait for several seasonal cycles to pass). In order to account for seasonality one has to integrate industry's seasonal pattern in the diffusion model. A method for incorporating seasonal patterns in any dynamic model was introduced in Radas and Shugan (1998). In this paper the author applies the later method on Bass diffusion model to forecast long-term sales of an air filter. This paper illustrates how to use the method and the adapted model, and also shows how the adapted model can be used to help answer managerially important questions. A variety of competitive scenarios are examined.

LITERATURE:

1. *Bass Frank M.:* "A New Product Growth Model For Consumer DurablesÊ" , Management Science, 15, 1969, pp. 215-227
2. *Crawford, C. Merle:* "New Products Management", 4th ed. Burr Ridge , IL: Richard D. Irvin, 1994.
3. *Dolan, R.:* "Managing the New Product Development Process", Reading, MA, Addison-Wesley Publishing Company, 1993.
4. *Radas, S. and S. M. Shugan:* "Seasonal Marketing and Timing New Product Introductions", Journal of Marketing Research, Vol 35, No. 3, August 1998, pp. 269-315.
5. *Urban, G. L. and J. R. Hauser:* "Design and Marketing of New Products, Englewood Cliffs, NJ: Prentice Hall, 1993.
6. *Bass F. M., T. V. Krishnan and D. C. Jain:* "Why the Bass Model Fits without Decision Variables", Marketing Science, Vol 13, No. 4, 1994, pp. 203-223.

PREDVIĐANJE ŽIVOTNOG VIJEKA NOVIH SEZONSKIH TRAJNIH DOBARA

Sažetak

Razvitak novog proizvoda izuzetno je važan za opstanak svake tvrtke. Zbog velikog rizika vezanoga uz inovacije, u praksi se koriste dobro osmišljenim programima razvitka. Jedan od ključnih sastojaka takvoga programa jest korištenje eksplicitnih modela za planiranje i predviđanje prodaje. Jedan je od popularnih modela za predviđanje dugoročne putanje prodaja Bassov model. Bassov model ne prepoznaje sezonalnost, pa zahtijeva podatke od nekoliko sezonskih ciklusa (obično godina).

U ovom je članku ponuđena nova verzija Bassovog modela u koju je ukomponirana sezonalnost. Time je značajno ubrzan proces primjene modela. Taj je novi model primijenjen na konkretnim podacima jedne američke tvrtke.