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Demand Forecasting of Short-life-cycle Products Based on Improved Generalized Norton-Bass Model

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Abstract: The shorter life cycle of products brings great challenges to the demand forecasting. This paper took a research on the value deteriorating short-life-cycle products. An improved Generalized Norton-Bass model was built for demand forecasting with consideration of the seasonal factor, price reduction and consumer behaviors in the market where multi-generational products coexist. Finally, a numerical experiment of three-generation MP3 products' sales was given, which proved that the improved GNB model could well forecast the demand of short-life-cycle products. And the analysis of the forecasting result was given.

1. Introduction

With the rapid development of science and technology, the modern products tend to be more and more convenient and intelligent. Continuous new products come out in the market, consumers' preferences change constantly, and the life cycle of products becomes shorter and shorter. For the typical short-life-cycle products, the upgrading speed of mobile phones is 3-6 months and 9-12 months for personal computers [1]. Generally, short-life-cycle products have the following characteristics: short life cycle, fast intangible metamorphism, strong demand uncertainty, seasonal demand, long production lead time, etc [2]. Demand forecasting of new products is essential [3], accurate demand forecasting could help retailers grasp the market trend, understand the consumers' motivation and behavior, arrange the ordering strategy and improve the profit of enterprise. Sun Han et al [4] analyzed the advantages of SVR in energy demand forecasting. Ni Dongmei et al [5] took fast-moving consumer goods as the research object, analyzed their demand influencing factors, established a multi-regression-integrated demand forecast synthesis model. Valeria B et al [6] assumed that the accuracy of product demand forecasting was related to the predictor's personal emotions and preferences. An experiment of Italian leather producer was conducted. Chongshou Li et al [7] took a fashion retailer in Singapore as an example to propose greedy method of aggregate decomposition to predict demand. Bass model and its improved ones also proved good performance in demand forecasting. Kaijie Zhu and Thonemann [8] established a prediction algorithm based on the BASS diffusion model and applied it to computer products. Xu Xianhao et al [9] used the Norton model to predict the market demand for short life cycle products. The model was expanded on the BASS forecasting model. Hakyeon L et al [10] proposed the integration of statistical and machine learning algorithms for the BASS diffusion model to forecast demand before new products are released. Xu Qi et al [11] used BASS model to establish a short-life product demand forecasting model based on historical sales data small sample.

In recent years, many experts have studied the short-life-cycle products with physical deterioration (decay, expiration, etc.). Few scholars have paid attention to the products with intangible value deterioration over time. Also, many existing research focus on the demand forecasting of value deteriorating products and ignore the complex market factors. This paper studied the short-life-cycle products with value deterioration. In the market where multiple generations of products coexist, the improved Generalized Norton-Bass model was proposed with consideration of seasonal factor, price factor and consumer behavior factors, so as to make demand forecasting for short life cycle products.

And in the numerical experiment, the improved model was used to fit the three generations of MP3 products (256MB, 512MB, 1G). The results showed a well fitting for the demand forecasting effect of short-life-cycle products.

2. Generalized Norton-Bass model

The Generalized Norton-Bass model (GNB model for short), was originally derived from a diffusion model proposed by Bass in 1969. In 1987, Norton and Bass proposed the Norton-Bass model (NB model for short) to describe the diffusion of multiple generations of products in the market. However, NB model does not differentiate those who have already adopted the old generation product from those who have not. The GNB model separates leapfrogging and switching, could better describe the actual market. Leapfrogging adopters refer to those may not have bought the previous generation products, but directly purchase the latest generation; switching adopters refer to those who possess the previous generation transfer to the new generation of products when the latest generation is introduced. The demand diffusion curve of the two generations of products in the market is shown in Fig. 1.

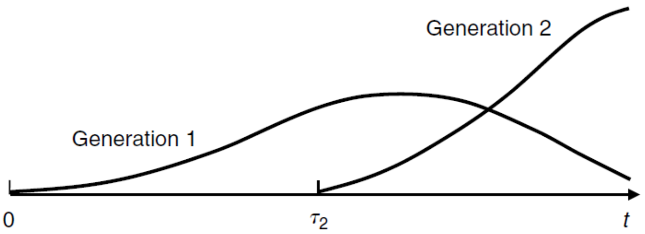

Fig 1. Diffusion curves of two generations of products coexist

As the GNB model, the *i*th generation introduced at time τ_i, the potential market is m_i and the cumulative number of adopters of every generation is $\Upsilon_i(t)$.

$$\begin{cases} \tilde{\Upsilon}_1(t) = m_1 F_1(t), & t \geq 0, i=1 \\ \tilde{\Upsilon}_i(t) = [m_i + \tilde{\Upsilon}_{i-1}(t)] F_i(t-\tau_i), & t \geq \tau_i, i \geq 2, \end{cases} \tag{1}$$

The formula of F_{G_i} could be obtained based on NB model.

$$F_{G_i}(\mathrm{t}) = \frac{1\text{-}e^{-(p_{G_i}+q_{G_i})t}}{1+(q_{G_i}/p_{G_i})e^{-(p_{G_i}+q_{G_i})t}} \tag{2}$$

Where $F_{G_i}(t)$ represents the diffusion of adoption of generation *i* at time *t*. p_{G_i} and q_{G_i} are the coefficient of innovation and coefficient of imitation for generation *i*.

3. Improved Generalized Norton-Bass model

This paper incorporates the seasonal factor, price factor and consumer behavior as parameters into the GNB model, so as to improve the accuracy of demand forecasting.

3.1 Seasonal Factor

Mobile phones show obvious seasonal influence on yearly sales. Assuming that S_i is the seasonal factor of generation *i*, q_{ij} means the sales of month *j* of generation *i*, Q_i is the yearly average sales of generation *i*.

$$S_i = \frac{q_{ij}}{Q_i} \qquad i \geq 2, 1 \leq j \leq 12 \tag{3}$$

3.2 Price Factor

Consumers are sensitive to price and products' price could influence the consumers whether to buy it or not. Some time after the new products introduced into the market, retailers would cut the products' price to stimulate the consumers' purchase. The price reduction function is as follows.

$$R_i(P_i) = (P_{i,0} - P_{i,t}) \tag{4}$$

Where $P_{i,t}$ is the price of generation *i* at time *t*. $t=0$ means the time product been firstly introduced into the market. The potential market which changes over time was modeled as follows.

$$\begin{aligned}
&PQ_1(t) = m_1 R_1(P_1)^{\lambda_1} \\
&PQ_2(t) = [m_2 + F_1(t)m_1]R_2(P_2)^{\lambda_2} \\
&PQ_3(t) = [m_3 + F_2(t-\tau_2)[m_2 + F_1(t)m_1]]R_3(P_3)^{\lambda_3} \\
&PQ_4(t) = [m_4 + F_3(t-\tau_3)[m_3 + F_2(t-\tau_2)[m_2 + F_1(t)m_1]]]R_4(P_4)^{\lambda_4}
\end{aligned} \tag{5}$$

Where λ_i is the coefficient of price elasticity and it changes with different life cycle demands of different generations of products.

3.3 Consumer Behavior Factor

The improved GNB model differentiates the leapfrogging adopters and switching adopters. The cumulative number of leapfrogging adopters $U_{i+1}(t)$ and switching adopters $W_{i+1}(t)$ of generation *i* are as follows.

$$\begin{aligned}
&U_{i+1}(t) = \int_{\tau_{i+1}}^{t} u_{i+1}(\theta)d\theta; \quad u_{i+1}(t) = \tilde{y}_i(t)F_{i+1}(t-\tau_{i+1}), \quad t \geq \tau_{i+1} \\
&W_{i+1}(t) = \int_{\tau_{i+1}}^{t} w_{i+1}(\theta)d\theta; \quad w_{i+1}(t) = \tilde{\Upsilon}_i(t) f_{i+1}(t-\tau_{i+1}), \quad t \geq \tau_{i+1}
\end{aligned} \tag{6}$$

Above all, we assume that there are four generations of products coexist in the market. Demand forecasting was taken with the improved GNB model. The function of cumulative number of every generation is as follows.

$$\begin{aligned}
&\Upsilon_1(t) = F_1(t)m_1[1-F_2(t-\tau_2)]S_1R_1(P_1)^{\lambda_1} \\
&\Upsilon_2(t) = F_2(t-\tau_2)[m_2 + F_1(t)m_1][1-F_3(t-\tau_3)]S_2R_2(P_2)^{\lambda_2} \\
&\Upsilon_3(t) = F_3(t-\tau_3)[m_3 + F_2(t-\tau_2)[m_2 + F_1(t)m_1]][1-F_4(t-\tau_4)]S_3R_3(P_3)^{\lambda_3} \\
&\Upsilon_4(t) = F_4(t-\tau_4)[m_4 + F_3(t-\tau_3)[m_3 + F_2(t-\tau_2)[m_2 + F_1(t)m_1]]]S_4R_4(P_4)^{\lambda_4}
\end{aligned} \tag{7}$$

4. Numerical example

This paper selects the sales data of 256M/512M/1G three generations of MP3 products during the 2^{nd} quarter of 2004 to the 4^{th} quarter of 2006. The data comes from the digital appliance industry analysis report in the China industry quarterly analysis report base of China economic information network.

4.1 Calculating Seasonal Factor

The products sales remain a stable status when they wenter the maturity period. Select the sales data of the maturity period of three generations products. Calculate the seasonal factor according to the Equation (3), results see the Table 1.

Table 1. Seasonal factors of new products

Quarter	1^{st} quarter	2^{nd} quarter	3^{rd} quarter	4^{th} quarter
Si	1.02	0.97	1.05	0.95

4.2 Calculating Price Factor

The new products have 4 generations. Its price reduction function is as follows.

$$R_4(P_4) = (P_{4,0} - P_{4,t}) \tag{8}$$

When the products first been introduced into the market. The retailers would not use sales strategy in the growth period. the price of the products would reduce to remain the market share. In this paper, we assumed that the products' price would decline 100 Yuan every three months after entering the maturity period. The coefficient of price elasticity of maturity period: $\lambda_4(m)$=0.01 , and The coefficient of price elasticity for the decline period $\lambda_4(d)$=0.005 .

4.3 Parameter Estimation p,q,m

The numerical example studied the sales forecasting of three generations of MP3 products and nine parameters are needed: $m_1, p_1, q_1, m_2, p_2, q_2, m_3, p_3, q_3$. In this paper, the simulated annealing algorithm is used to estimate the parameters. The parameters estimation value are calculated by 1stopt software and the results shown in Table 2. The range of parameters are $m_i \in [200, 2000]$, $p_i, q_i \in [0,1]$.

Table 2. Parameters estimation of three generations

No.	Parameters	Estimation results
1	Max market potential (m_1)	814.4935
2	Innovation coefficient (p_1)	0.0213
3	Imitation coefficient (q_1)	0.2992
4	Correlation coefficient	0.9978
5	Max market potential (m_2)	2034.1651
6	Innovation coefficient (p_2)	0.0051
7	Imitation coefficient (q_2)	0.3989
8	Correlation coefficient	0.9991
9	Max market potential (m_3)	174.9564
10	Innovation coefficient (p_3)	0.0266
11	Imitation coefficient (q_3)	0.3517
12	Correlation coefficient	0.9989

4.4 Demand Forecasting and Analysis

Table 3. Demand forecasting results of three products (unit: ten thousand)

Time	2007				2008			
	1st quarter	2nd quarter	3rd quarter	4th quarter	1st quarter	2nd quarter	3rd quarter	4th quarter
t	12	13	14	15	16	17	18	19
256M (NB)	419.2	387.64	338.86	280.71	221.50	167.60	122.60	87.444
256M (Improved GNB)	449.70	405.53	384.96	303.56	241.74	196.79	132.12	85.23
512M (NB)	434.50	464.60	458.69	419.87	359.20	290.40	224.30	167.38
512M (Improved GNB)	446.48	475.06	510.85	472.55	429.27	341.70	244.03	184.82
1G (NB)	390.90	584.37	815.96	1065.7	1309.0	1527.0	1708.0	1850.3

Time	2007				2008			
	***1st* quarter**	***2nd* quarter**	***3rd* quarter**	***4th* quarter**	***1st* quarter**	***2nd* quarter**	***3rd* quarter**	***4th* quarter**
1G(Improved GNB)	407.64	624.14	874.5	1185.2	1479.4	1698.5	1876.5	1981.1

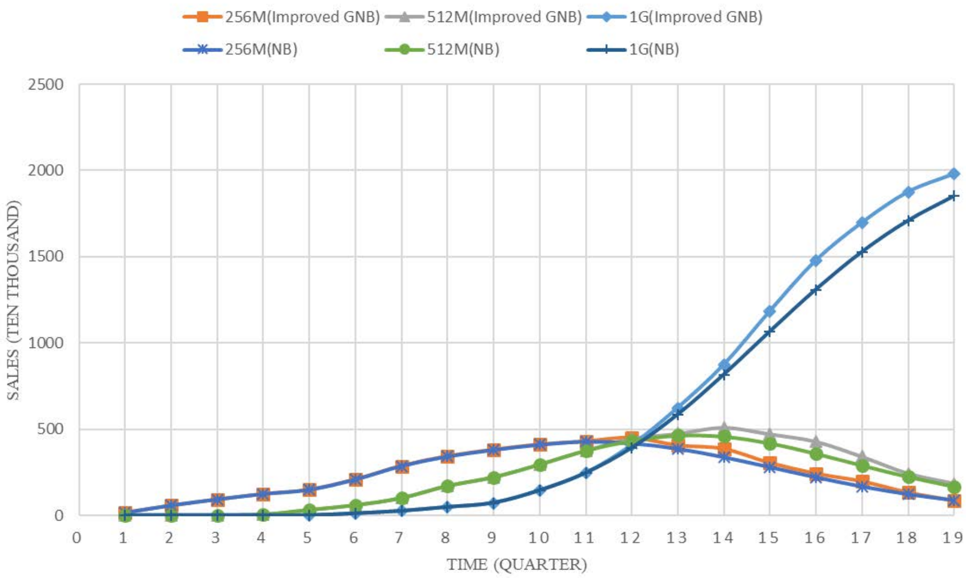

Fig 2. Fitting curve of demand forecasting of three products (NB, Improved GNB model)

Based on the above estimated parameters value, this paper incorporates the complex market factors, such as the seasonal factor, price factor, consumer behavior, follows the demand forecasting of three generations products during 2007-2008. Table 3 shows the demand forecasting comparison of the NB model and the improved GNB model. And the data fitting curves see Fig. 2.

As we can see in the figure, the improved GNB model has a similar fitting demand with NB model. And both of the two models reflect the actual conditions that new products replace the old ones when multiple generations products coexist in the market. Based on the NB model, the improved GNB model makes great progress. The improved GNB model considers the complex market factors such as seasonal factor and price factor. The 1G MP3 product shows a continuous uptrend in the last, because the assuming market does not appear the next generation which could replace it. Actually, this condition does not exist in the real competitive market.

5. Conclusion

The life cycle of products becomes shorter and shorter, the traditional demand forecasting methods ignore the characteristics of the short-life-cycle products and the forecasting accuracy cannot meet the requirements. In this paper, an improved Generalized Norton-Bass model was built and used to empirically study the diffusion of multi-generation MP3 products in the market. Based on the NB model, the improved GNB model takes into account the influence of seasonal factors and price reduction strategies on product sales, which could better describe the actual market. The results show that the model has a good fitting effect on the market demand forecasting of multi-generation MP3 products. MP3 is a typical short-life-cycle product, which also shows that the improved GNB model has a good application prospect for the demand forecasting of multi-generation short-life-cycle products. After the new products are introduced into the market, what kind of substitution effect will appear on the old products? What is the diffusion route of the short-life-cycle products are in the recession period? How to make the ordering strategy according to the demand, etc., these questions are all worthy of further research.

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