Life Cycle Prediction for Agile Supply Chains: A Comparison of Methods

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Abstract

The aim of this paper is to compare the performance of several product life cycle models on an empirical dataset from a lighting products retailer to inform inventory decisions for products that are in different life cycle stages: introduction, growth, maturity, or decline. Bass diffusion curves, piece-wise linear curves, and polynomial curves, fourth order polynomial curves are used to predict the life cycles of 2,618 products. We identify which products need an efficient and which require an agile supply chain design. We provide recommendations for how much inventory to keep, especially for products that are in the decline stage.

Keywords: Bass Diffusion Model, Piece-wise Linear Curves, Life Cycle Prediction

Introduction

Product life cycle estimation has been one of the most elusive activities for supply chain planners. We observe a negative correlation between product life cycles and the level of globalisation: increasing demands from customers and reducing lead times to respond to changes in the supply chain (Singh, 2015). Retail supply chain experts interviewed highlight the increasing importance of new products with short life cycles (Fildes et al., 2022).

The aim of this paper is to compare the performance of available product life cycle models on an empirical dataset from a lighting products retailer to inform inventory decisions for products that are in different life cycle stages: introduction, growth, maturity, decline. We present an approach to forecasting the demand for new products that are similar to past products by fitting product life cycle curves to historical demand.

We test several of the methodologies proposed in the literature for life cycle prediction to assess their applicability and prediction accuracy for an empirical dataset from a lighting products company. The reason for using a range of methodologies is to establish which methodology performs better for the company and then choose the best performing method to inform subsequent operational decisions such as inventory planning.

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One of the significant impacts of globalisation is increasing product variety, putting pressure on supply chain management by increasing the number of strategic, tactical, and operational decisions to take. In the presence of wide product portfolios, which are usually in the order of thousands or tens of thousands, manual management of products are infeasible. Hence, we need robust methods to help manage product portfolios and assist in product distribution decisions along the different stages of a product's life cycle.

The research question for this paper is the following: Which models give the highest accuracy when predicting sales of a product, or a group of products along different stages of the life cycle? We contribute to knowledge by empirically testing five frequently used models to predict the sales of a product along with its product life. In a portfolio of 2618 lighting products, there is no single model that fits the best. Hence, we underline the need for automated decision support systems which can select the applicable tool based on the market response to a product. When a new product is introduced to the portfolio, the predictions for the group of similar products can be used to predict its life cycle.

Literature Review

The increasing challenge of product complexity along with the dynamism of products globally affects PLC for companies in the technology industry. This pushes companies to rethink and adopt lifecycle management (PLM) concepts in order to assist the management of operations and address the complications of the development of new products. PLM can be defined as a unified, information-based method that consists of people, processes, and technology towards the entire aspect of a product's life (Gmelin and Seuring, 2014).

Liu et al. (2020) provide a special issue consisting of 12 papers on product lifecycle management (PLM) covering themes on important elements for sustainable smart manufacturing PLM, effective usage of smart technologies for sharing and integrating data and manufacturing in different PLC and to sustain PLM, and finally, benefits for enabling smart technologies into the entire PLC stages.

Restuccia et al. (2016) conduct an in-depth interview to explore and develop knowledge on PLM focusing on the manufacturer-distributor interface. Their findings contribute to new product development (NDP) to plan for distributor involvement in PLM-related activities since distributors play a significant role in incremental innovations.

There has been a strand of research combining PLC and manufacturing processes and in particular, analysing joint forecasting and inventory management (Hu et al., 2019). Initially, Kurawarwala and Matsuo (1996) used a bass diffusion model to formulate a growth model to forecast the life-cycle demand of short life-cycle short life-cycle products with seasonality including sales without history.

Gallien et al. (2015) examined the restocking flexibilities of new product launches while considering previous forecasts as part of inventory control. Their approach of combining PLC and inventory management yielded a 2% increase in average sales and a 4% reduction in unsold units at the end of the regular selling season for Zara.

Similar to the work of Kurawarwala and Matsuo (1996) but with methodological variations, Hu et al. (2019) considered computers and PLC curves, focusing on out-of-sample testing of PLC curve forecasts of Dell's products. In addition to the Bass curves (i.e., the bell shape of the diffusion model), they included polynomial and piecewise-linear curves in their empirical analysis, which suggest that data-driven clustering of simple triangles and trapezoids performs best for forecasting, resulting in mean absolute errors approximately 2%–3% below Dell's forecasts.

Acimovic et al. (2019) provide data and then use an analytical approach to exemplify how data-driven PLC is cleaned, normalized, and analyzed throughout the PLC stages. Their work considered seasonal adjustments, and other relevant modifications needed when exploring different aspects of the PLC. Polynomials and piecewise linear models are parametric curve models that are empirically tested (Lei et al., 2022). These models perform well for products with a sales history.

Methodology

We have 2618 products from a lighting company with two years of monthly sales data. We do not have promotional information on these products; however, the products are unlikely to be subject to promotions like those observed for fast moving consumer products as they are needed for lighting projects and unlikely to create impulse buys. We group the products under four meaningful categories such as lights, LEDs, lamps, and complementary products. An example of lights is satin nickel fixed pressed downlight, an example of LEDs is blue marker LED, an example of lamps is triple compact white lamp, and an example of complementary products is electronic transformer.

Before fitting product life cycle curves, we cleaned the data and excluded any SKU without any demand in the past two years, assuming these SKUs already declined owing to the lack of demand. Then, we normalise the data so that for each product, the cumulative sum of customer orders along its lifetime is equal to 1 (Acimovic et al., 2019) before fitting five models to observed sales series and choosing the model with the highest accuracy. This normalisation allows the life cycles of products with dramatically different volumes to be comparable.

Bass diffusion curves, piece-wise linear curves, and polynomial curves, fourth order polynomial curves are used to predict the life cycles of products in the consumer electronics sector (Hu et al., 2019). We fit Bass diffusion curves (Bass, 2004), second, third, and fourth order polynomials and piece-wise linear curves to stock keeping units (SKU) of a company in the lighting sector. These products tend to have longer life cycles than products in the consumer electronics sector.

Findings

After cleaning the data, we had 2618 SKUs for which we had the monthly sales history for the past two years. Before fitting the models, we normalised the sales, so that each period showed the percentage of sales. We compared the performance of five models based on the Root Mean Squared Error (RMSE) in Table 1.

Table 1 – RMSE of Fitted Product Life Cycle Curves

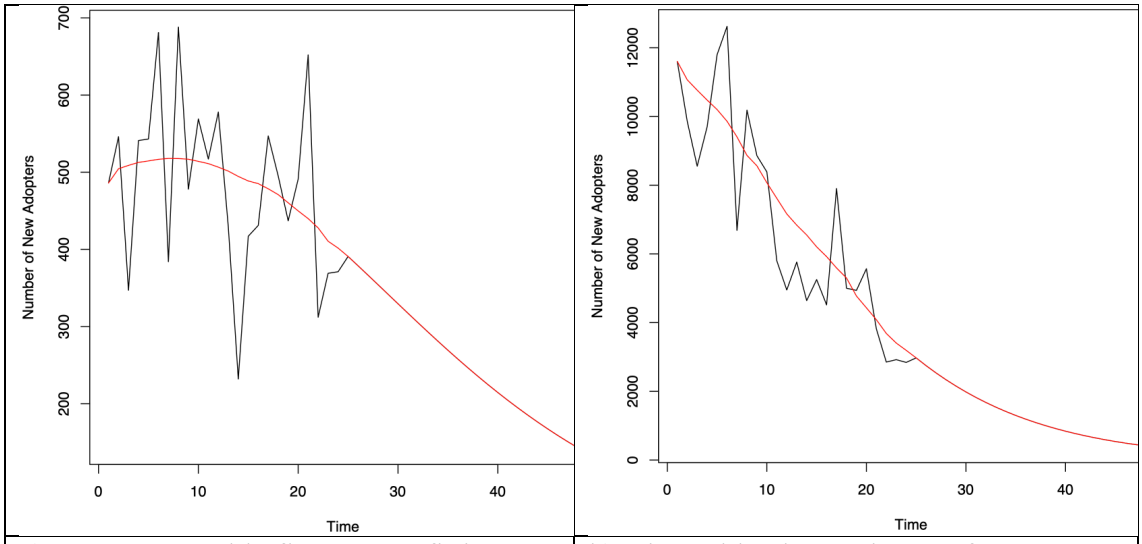
Code	Predicted end of life	Bass	Poly2	Poly3	Poly4	Triangle	Min Error
SKU1	100	0.0116	0.0119	0.0119	0.0097	0.0024	Triangle
SKU26	66	0.0114	0.0114	0.0114	0.0112	0.0124	Polynomial4
SKU44	58	0.0098	0.0102	0.0100	0.0099	0.0608	Bass

The RMSEs in Table 1 are quite close. Of the 2618 SKUs, we were able to fit a Bass diffusion model to 2215 of them. Similarly, we were able to fit a triangle model to 2332 SKUs. Table 2 shows the distribution of best performing models across the analysis dataset.

Table 2 – Distribution of Product Life Cycle Curves

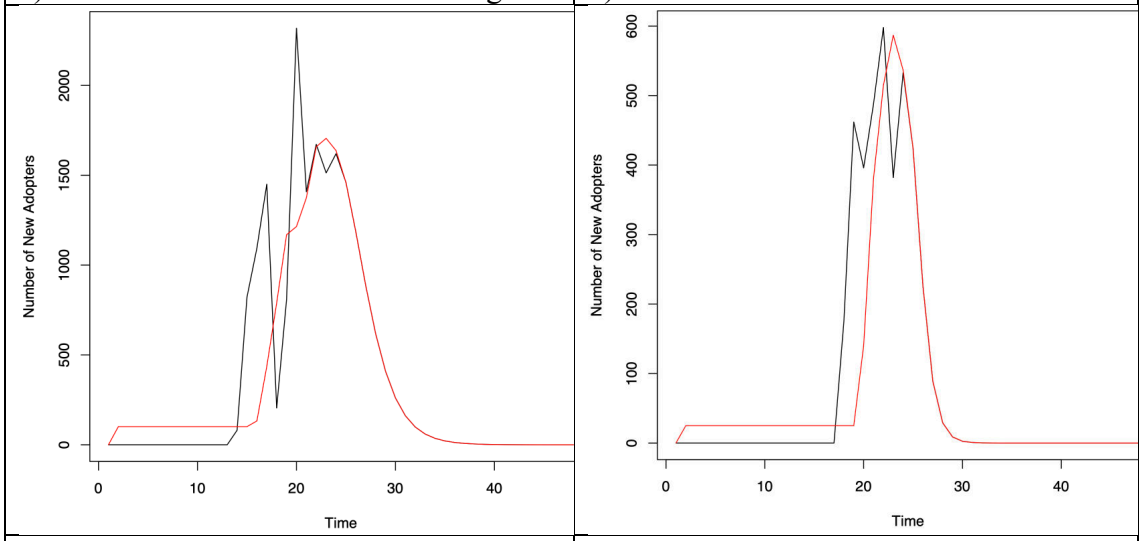
	Number of SKUs	Percentage of SKUs
Triangle	1026	39%
4th Order Polynomial	1090	42%
Bass	502	19%
Total	2618	100%

Similar to Hu et al. (2015)'s work, 4th order polynomial was the best fit prediction for 42% of the SKUs in Table 2. It is followed by triangle distribution and Bass Diffusion model. At 19%, Bass diffusion model applies to 502 SKUs, so it is worth considering in product life cycle predictions. Figure 1 shows Bass diffusion models of four products; a) and b) that already reached maturity and c) and d) new products introduced relatively late in the analysis period.



a) Interconnectable fluorescent fitting

b) Dimmable electronic transformer



c) Anodised aluminium fluorescent post light

d) Non-dimmable LED lamp

Figure 1 – Bass diffusion curves of selected products

In Figure 1, the predicted end of life of the interconnectable fluorescent fitting product in a) is 91 whereas the predicted end of life of the dimmable electronic transformer in b) is 59. The anodised aluminium fluorescent post light in c) was introduced to the market in period 14 and its expected end of life is period 36. The non-dimmable LED lamp in d) was introduced in period 18 and its predicted end of life is period 30. While an efficient supply chain is more appropriate for products similar to those given in Figure 1 a) and b), a more agile supply chain design is needed for products given in c) and d).

Life Cycle Prediction by Clusters

Based on product definitions, we cluster 2618 products into four clusters: 1) Lights 2) LEDs, 3) Lamps, and 4) Complementary products that are needed to install lights, LEDs, or lamps. The distribution of products into these clusters is given in Table 3. In this table, the product life duration is given in months.

Table 3 – Distribution of Products into Clusters

	Number of SKUs	Percentage of SKUs	Min End of Life	Average End of Life	Std. Dev. of End of Life
Lights	1010	39%	11	43.2	24.4
LEDs	650	25%	11	40.9	24.7
Lamps	484	18%	9	40.5	23.3
Complementary Products	474	18%	14	47.7	24.0
Total	2618	100%	9	42.9	24.3

Discussion

The classical Bass model has been used widely and extended to accommodate market conditions and firm characteristics, such as the presence of a monopoly or the firm's being a public or a private one (Tigert and Farivar, 1981). Using several models to estimate product life cycle introduces a structured approach to analysing market potential for products and help support decisions around how many to stock and how often to replenish.

The Bass diffusion curve is worth considering in life cycle predictions owing to its robustness in predicting market potential based on the proportion of adopters and imitators. It uses a generalised logistic curve to predict the diffusion of an innovation, i.e., a new product which will be adopted early by some and later by some others. Nevertheless, the estimate of the market potential should be subjected to plausibility tests (Tigert and Farivar, 1981).

Supply chains need to be agile and responsive to meet dynamic market requirements (Singh, 2015). By being able to estimate the growth, maturity, and decline phases of products, the inventory decisions of whether to stock or not to stock an product and in the case of stocking decisions, how many to stock can be made more accurately.

Conclusions

Our work contributes to the product life cycle forecasting literature, showing the applicability of a range of methods to predict the life cycle of a product with a ranking of these methods based on accuracy of prediction. One of the challenges for planners is to decide how much inventory to keep, especially for products that are in the decline stage. The next step in this research is to predict the life cycle stage of the products to assist managers in their inventory decisions.

Practical implications of this research suggest that managers consider the life cycle stages when they make inventory management decisions. The ability to predict different life cycle stages for a product allows taking bold inventory decisions to minimise the left-over inventory at the end of the product's life. Our approach is beneficial especially for products with a new version or an upgrade introduced every couple of years.

Our research has some limitations. We currently do not consider promotion effects on the sales along the life cycle, but we find it a potential area of research to pursue as an extension. Bayesian functional regression has been applied to incorporate promotion effects into the product life cycle (Lei et al., 2022). This modelling approach can generate dynamic forecasts by incorporating new sales data. It is widely used for forecasting in a range of sectors.

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