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A survey on short life cycle time series forecasting

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ABSTRACT

The life cycle of products is becoming shorter and shorter due to increased competition in market, shorter product development time and increased product diversity. Short life cycles are normal in retail industry, style business, entertainment media, and telecom and semiconductor industry. The subject of accurate forecasting for demand of short lifecycle products is of special enthusiasm for many researchers and organizations. Due to short life cycle of products the amount of historical data that is available for forecasting is very minimal or even absent when new or modified products are launched in market. The companies dealing with such products want to increase the accuracy in demand forecasting so that they can utilize the full potential of the market at the same time do not oversupply. This paper presents a review of the recent innovations for forecasting of short lifecycle or new products. The intention of the analysis is to examine the general outline of work done in forecasting of short lifecycle products using data mining, Segmentation and clustering, structured judgment and statistical forecasting.

Keywords: -Short life cycle product, time series, forecast, structured judgment.

1. INTRODUCTION

Product life cycle is defined as the time period over which a product is designed, developed, brought to market and then eventually removed from market. It involves five distinct stages: product development, introduction, growth, maturity and decline. Consumer products can be divided into two types of products based on their availability in market and their demand patterns: basic or convenience products and luxury or seasonal products. Basic products are staple goods which have long life cycle and large amount of historical data and are easy to forecast using standard methods. Seasonal products on the other hand have short life cycle with little or no historical data. Seasonal product life cycles are measured in months rather than years. The products with short time period demand are categorized as short life cycle products. These products become obsolete soon leading to very short time series. Consumer electronics, computers, video games, semiconductor industry, fashion products, movies are examples of short life cycle time series. The lifecycles can vary from few weeks to few years. Due to shorter life cycles historical sales or other related information is available for short duration of time. This shows that short life cycle products need different forecasting methods than basic products. Also the launch of new product is extremely difficult to forecast. The life cycle of a new product is mostly described by slow growth when the product is introduced in the market followed by a phase of fast development, thereafter the demand for product becomes stable and the product moves in stage of maturity; finally there is swift drop in demand and the product is removed from the market and replaced by another product [1] [2]. There is an uncertainty associated with the launch of new product which makes the forecasting difficult. Generating forecasts becomes difficult and challenging task because of the unavailability of historical data and the short lifecycle of the similar products. Most of the existing forecasting models are not able to deal with the uncertainty in the demand patterns. Because of such an uncertainty and lack of historical data traditional forecasting methods do not work.

This paper surveys the advantages and disadvantages of a series of short life cycle forecasting techniques along with new product forecasting. These techniques include Bayesian methods and diffusion models, machine learning, logistics and Gompertz models, Bass Model, coordinated ordering decisions, management judgment, segmentation and clustering.

The paper starts with literature on short life cycle product time series and the challenges faced during forecasting of short lifecycle products. Subsequently, we introduce various strategies of short life cycle product forecasting, followed by the critical discussion on the pros and cons of different approaches. Finally we conclude the paper by stating the possibility of future research.

2. SHORT LIFE CYCLE TIME SERIES

Kotler, Wong, Saunders and Armstrong (2005) define product life cycle as the course of a product's sales and profits over its lifetime [3]. Albeit over the life of a product, an organization does not know how the demand will change in future but it will normally follow the life cycle curve going through various phases of product lifecycle as is mentioned in literature [4]-[6]. A product's lifecycle incorporates four different stages, for example, Introduction, Growth, Maturity furthermore, Decline [7]. Figure 1 depicts the typical life cycle of a product.

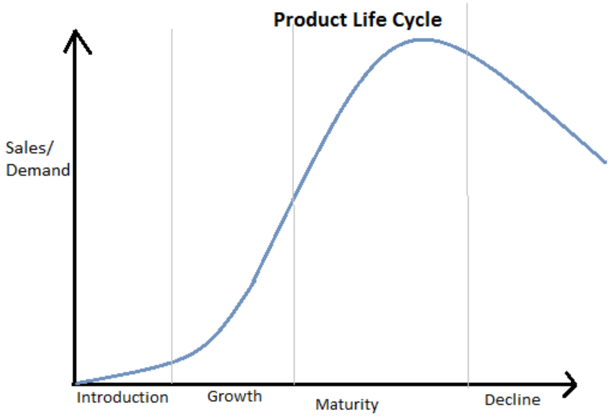

Figure 3 Product Life cycle.

1. **Introduction:** Once the product is dispatched into marketplace there is slow increment in sales as product is introduced.
2. **Growth:** in this phase the product is established in marketplace and there is rise in sales.
3. **Maturity:** after the product is well established and accepted by majority of the potential buyers, the market is saturated the sale of the product slows down.
4. **Decline:** in this phase the sale goes down drastically and the product no longer makes profit. After this phase the product is replaced by another product.

Short lifecycle time series have a very high uncertainty and volatility of demand. An additional problem related to short lifecycle forecasting is inadequacy of historical data. In case of new product forecasting there is complete unavailability of any previous data related to the product, which makes forecasting such products a complex process. In spite of availability of large number of methods for forecasting nonlinear time series, these techniques cannot be used. These methods require large amount of historical data for generating accurate forecasts. Traditional forecasting methods like ARIMA don't prove useful either because short life cycle products do not satisfy the assumptions of these methods or it is difficult to accurately estimate the parameters of such methods with lack of historical data.
The time series of short lifecycle products may even have a complex shape (see Figure 2) which may not necessarily be similar to bell shaped pattern. This makes forecasting even more difficult and there is a need for defining such a methodology which can be applied to any form of SLP time series.

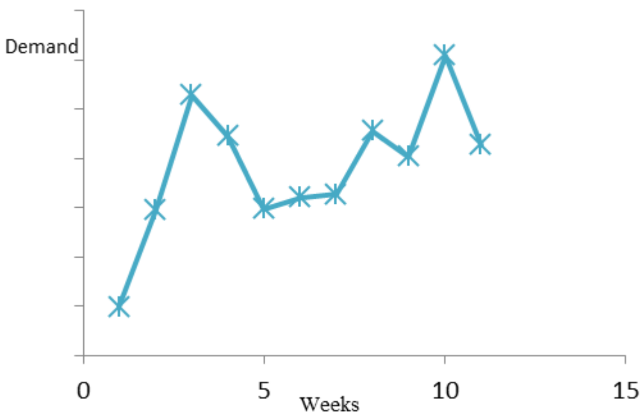

Figure 2 Non bell-shaped pattern of a short life-cycle time series.

These problems make it necessary to develop forecasting approaches specifically for short life cycle time series products. The forecasting approach should overcome all the difficulties faced in forecasting this type of products.

3. STRATEGIES FOR SHORT LIFE CYCLE FORECASTING

This section presents a review of the general work done in forecasting of short lifecycle products. This is intended to give the general summary of the current status of research and discuss the scope for future research.

3.1 Forecast based on diffusion models

Mead and Islam, 2006, state that diffusion models are being used since 1960 to forecast the diffusion of innovations [2]. Since these models are used for new product forecasting, these models can even be applied to SLCP. Three very popular diffusion models are: Gompertz, logistics and Bass models. All the three models use S-Shaped curve to represent the cumulative diffusion and the curve flattens as the product reaches the maturity phase. Trappey & Wu (2008) present a comparison of the time varying extended logistic, simple logistic, and Gompertz models [1]. In their research they have analysed the results for electronic products time series. The model parameters are determined using linear and non-linear least squares method. The authors found that the time varying extended logistic was the best fit and gave accurate predictions. Gompertz models had the second best forecasting error.
Kurawarwala & Matsuo (1998) have presented the analysis of three models: the linear growth model, the Bass model, and the seasonal trend Bass model [8]. Dataset used for the analysis is the demand data of personal computers. The models are compared based on performance measures like sum of square error (SSE), root mean square error (RMSE), mean absolute deviation (MAD). The seasonal trend Bass model has the minimum forecast error.
Wu & Aytac (2008) propose a forecast procedure using Bayesian updating and combining forecasts of different diffusion models [9]. Data set used is semiconductor demand time series. A priori forecast is made using the existing growth models. Then a sampling distribution is obtained by applying the growth models on time series of similar products. Finally, Bayesian updating is performed and the final forecast is obtained as a combination of the different growth models in the a posteriori results. Advantage of this method is that there is systematic reduction of variance in the final forecast. A similar work is presented in Wu *et al.* (2009).
Adaptive forecast procedure for short lifecycle products is proposed by Zhu & Thonemann (2004) [10]. The authors have used the Bass diffusion model. The parameters are estimated using non-linear least square estimation and the authors propose to update the parameters using Bayesian approach. Datasets of personal computers are used for forecasting and the results are examined using MAD. The proposed method accomplishes better results than the double exponential smoothing and the Bass model.
The problem with diffusion models is that market may react very differently for similar products. Also the selection of analogues products is problematic as it depends on judgement. Additional issue specific to diffusion models is the complexity of adoption curves for high tech products.

3.2 Forecast based on machine learning models

According to Zhang et al. (1998) machine learning methods such as neural networks are widely used in forecasting activities [11]. Clustering and classification algorithms are used to extract necessary information from time series data. Hence they can be used for finding similar time series.
Xu & Zhang (2008) [12] have proposed the use of Support Vector Machine (SVM) to forecast time series with inadequate data. They have used computer product dataset for their research. The authors take into account the past values of demand and seasonal factors. The results are analysed using RMSE and MAD. As per results the proposed model outperforms the Bass model.
Meade & Islam (2006) uses a multilayer feed forward neural network accommodated for prediction and a controlled recurrent neural network to predict short time series [2]. The authors observe that in one step ahead forecasts a multilayer feed forward neural network accommodated for prediction performs better. But in the case of two step ahead forecasts the controlled recurrent neural network improves the feed forward neural network.
A major drawback of neural networks is that they require lot of parameters to be set up. Also there is no standard procedure to set up these parameters to ensure a good network performance. As mentioned by Zhang *et al.,* 2001 [13], the lack of systematic approach is the major cause for inconsistencies in the findings of neural networks. Also the neural networks are very time consuming and hence cannot be applied for fast changing market of fashion products or hi-tech products.

3.3 Forecast based on similar products

The unavailability of information for short lifecycle products is compensated by using the data of similar products for which sufficient history is available.

Thomassey & Fiordaliso (2006) have come up with clustering and classification based forecasting procedure for new products [14]. Initially, the time series are grouped together based on clustering procedure followed by classification procedure which classifies the new products in a specified cluster. The centroids of the cluster to which the new product belongs represent the forecasted sales. The authors have used textile fashion products dataset. A similar work is presented by Thomassey & Happiette (2007) [15].

Szozda (2010) proposes forecasting using analogous products [16]. The author first finds the analogous product; product having highest similarity in terms of sales figures with the new product. Calibration and adjustment of time series is done to maximize the similarity measure. Calibration is used to change the volume of sales while adjusting the length changes the length of the lifecycle being compared. The author has used sales dataset of similar products in European markets. The results are analysed using MSE and the proposed method produces forecasts with forecast error less than 10%.

3.4 Forecast based on Structured Judgment

Graefe and Armstrong (2011) have proposed a human judgement approach for forecasting short life cycle products with lack of any historical data [17]. Human judgement can be either individual manager judgement or group of managers' judgement. The application of only management judgement for forecasting has several issues. Managers have difficulty in deducing even simple linear patterns in historical data and so they can not accurately identify the complex nonlinear patterns in the data. Also the managers may be biased or may have unrealistic views about the products which may mislead the forecasts. Judgement by group of managers instead of individual managers can help in reducing biases. Different methods for group judgements could be maintaining minimal groups, conducting face-to-face meetings, preference markets. These methods too have drawbacks that a group is difficult to maintain; also due to peer pressure all members in the group may not express their own ideas.

Leonard et al. (2007) have come up with a strategy which combines analytics with structured judgement for forecasting new products [18]. The authors suggest using domain knowledge along with statistical analysis of time series data to improve the forecasting efficiency. The authors have come up with patent pending application which combines data, analytics (statistical forecasting, clustering) and domain knowledge using point-and-click technology. They have used consumer packaged goods dataset for their analysis. The results were examined by comparing RMSE, MAPE, Akaike information criterion etc. The structured judgement approach improved the accuracy of forecast by 15% and also reduced the forecasting time. The authors further suggest text analytics for sentiment analysis to analyse and integrate unstructured data (tweets, product reviews, Facebook posts and other internet-generated information) in decision making.

4. CONCLUSION

In this paper we have studied various approaches that could be applied to short life cycle time series forecasting. Based on the literature survey it is observed that no one approach is sufficient for short life-cycle forecasting and we need to combine two or more approaches for achieving the desired accuracy. Ensemble methods have worked in other areas of forecasting and it is a subject of study for future researchers to analyse if this approach can be applied to short lifecycle forecasting. And if such approaches can be applied then how such combinations can be implemented to give most accurate results.

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