IJBPAS, September, 2016, 5(9): 2027-2033

ISSN: 2277–4998

International Journal of Biology, Pharmacy and Allied Sciences (IJBPAS)

'A Bridge Between Laboratory and Reader'

www.ijbpas.com

FACTORY CUSTOMER DEMAND FORECASTING USING SALES DATA EXTRACTION AND ANALYSIS OF ASSOCIATION RULE

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Received 26th May 2016; Revised 10th June 2016; Accepted 26th July 2016; Available online 1st Sept. 2016

ABSTRACT

Most businesses often try to avoid unpredictability of demand since they need to plan efficiently for future sales. Given this, the process of demand forecasting has grown in relevance as companies are increasingly applying techniques to forecast demand so as to plan for sales. Although a range of techniques exists in literature as shown, it is difficult to find the one that assures the accuracy of the forecasts. The aim of this study is to evaluate the various forecasting techniques available. The methodology applied in this study is a qualitative study into various literature sources to determine the various sales forecasting techniques used in conjunction with promotional methods as the chosen associated rules in the process of demand forecasting.

Keywords: Customer Demand Forecasting, Sales Data, historical sales data

INTRODUCTION

The capacity for a company for forecast demand for products in the future determines the quantity of sales they are likely to make. The process of demand forecasting is quite intricate, and many companies often get it wrong, which eventually leads to poor planning that may affect the sustainability of such firms (Navarro-Barrientos, Armbruster, Li, Dempsey, & Kempf, 2014). Although there is a range of techniques available to forecast the demand for a company's product, each method depends on the compatibility of the situation at hand. The importance of demand forecasting cannot be rubbished since it determines what may happen to a firm's present product sales (Nenni, Giustiniano, & Pirolo, 2013). Therefore, it is important to choose the most suitable method of forecasting, preferably one that takes a multi-functional approach.

Customer demand forecasting is a complex process that incorporates many inter-related variables (Chae, 2015). However, an essential variable is the historical sales of a company. Aside from the past sales, other factors can be treated as associated rules, which can also be used in conjunction with the analysis of historical sales data to project on the customers' demand for a company. The objective of this study is to examine the use of sales forecasting and promotional information, as the associate rule chosen, to forecast on customer demand.

Marketing analysts are often called upon to comprehend the interactions that exist between latent inter-related variables. A typical instance is observed in grocery retailers that depend on precise sales forecasts at Stock Keeping Unit (SKU) level in generating business decisions in a vast myriad of areas that include finance, inventory, production, and marketing (Fleischmann, Meyr, & Wagner, 2015). The demand forecasting accuracy is influenced by various sources of information that entail inter-category promotion schedules, intra-category promotion schedule, and product sales history. The process of building models for product sales forecasting takes into consideration many factors (Kiflu & Lopez, 2015). It is prudent to consider the type of information to be integrated into the forecasting model, the degree to which the information inputted influences the forecasting accuracy, and finally the ways of manipulating the inputted high dimensional information for purposes of generating better forecasts.

METHOD

The methodology applied in this study is a qualitative study into various literature sources to determine the various sales forecasting techniques used in conjunction with promotional methods as the chosen associated rules in the process of demand forecasting. In this line, this study looks at the forecasting models in the various literature that integrate historical sales and promotional variables as the essential variable although models that integrate other periphery aspects can be considered pertinent as well.

Based on the outcomes of the literature search, a comprehensive analysis will be conducted in the subsequent section. The results of the experiment are related to the retail sector, thus, would apply to any factory that can be categorized as part of the retail sector. As such, the outcomes are just generalized for enterprises within the retail sector.

RESULTS AND DISCUSSION

The outcomes of the search revealed that SKU sales techniques are univariate forecasting models (Kilger, Reuter, & Stadtler, 2015). They are based on time series methods, which evaluate historical sales for purposes of extracting a demand trend that projects into the future. The findings revealed a myriad of methods used in demand forecasting. They include simple moving averages, exponential smoothing averages, and the Exponential smoothing space technique. These techniques do not consider external factors, for instance, promotions and price changes into account.

Simple time series techniques operate effectively for durations in which there are no promotions (Khasanah, Lin, & Kuo, 2013). On the other hand, models that have more inputs during the periods of promotion are more likely to enhance accuracy to sustainable levels. Given these differences, many studies often use the univariate forecasting techniques as a benchmark model to weight the accuracy of integrating sales analysis and promotion or where just sales analysis is applied to project on the future demand patterns.

The outcomes of this study showed that the incorporation of focal product's promotional variables as part of the models applied for forecasting improves sales forecasting in which promotion variables are used (Oksanen, 2015). From a practical perspective, a majority of retailers often apply the base-times-lift approach when forecasting on the sale of products at the SKU level. This technique basically incorporates a two -step procedure. The first functioning of the model is that it creates a baseline forecast just from a simple time series model.

This baseline forecast only takes into consideration the historical sales of a company. Thus, the demand pattern developed at this stage only concerns the sales (Williams, Roh, Tokar, & Swink, 2013). However, as earlier stated, many variables other than historical sales affect demand forecasting. This concept leads to the second step of the procedure. This second stage encompasses adjusting the demand projections for anticipated as well as incoming promotional events.

The estimations of the adjustments form their basis from the lift effect caused by recent promotions or price reductions (Ho & Choi, 2014). Such estimations are also dependent on the entrepreneurial judgments of the brand managers. Other studies also proposed a model-based forecasting system, which considers promotional data, to forecast sales. Such techniques relate to multiple regression models that have exogenous inputs, which correspond to the core promotional features of the product in question.

One promotion-event forecasting system found in the study is PromoCast. This technique integrates a static cross-sectional regression evaluation of SKU-store sales that have a range of promotion conditions (Saha, Lam, & Boldrin, 2014). This technique also uses information that relates to chain and store historical performance of the given company. Although the technique proved to be important as it involves many variables, it exhibited some drawbacks as well. One of these limitations of these studies is that they fail to acknowledge the significance of promotions and price reductions of substitutes or complementary products.

Another forecasting technique observed from the studies that integrate the promotional information of influential products is the SCAN*pro model (Thomopoulos, 2015). This model is a solution to the problem of the other techniques that only took the pricing and promotional features of the product at hand but never acknowledged the influence of influential products. Aside from the pricing and promotion variables, this model integrates other factors such as store effects, week effects, aisle displays, and feature advertising.

Studies have also shown that the CHAN4CAST is another renowned forecasting model that integrates some variables likely to increase the accuracy of demand forecast at the SKU level (Jaipuria & Mahapatra, 2014). However, this technique is different from the ones previously discussed as it applies the regression model. This model captures the influences of a range of variable pertinent to the sale of products. These variables include seasonality, company promotional variable, competitor promotional variable, company prices, competitor prices, and the historical sales of a company. The image below shows typical regression models such as the one described.

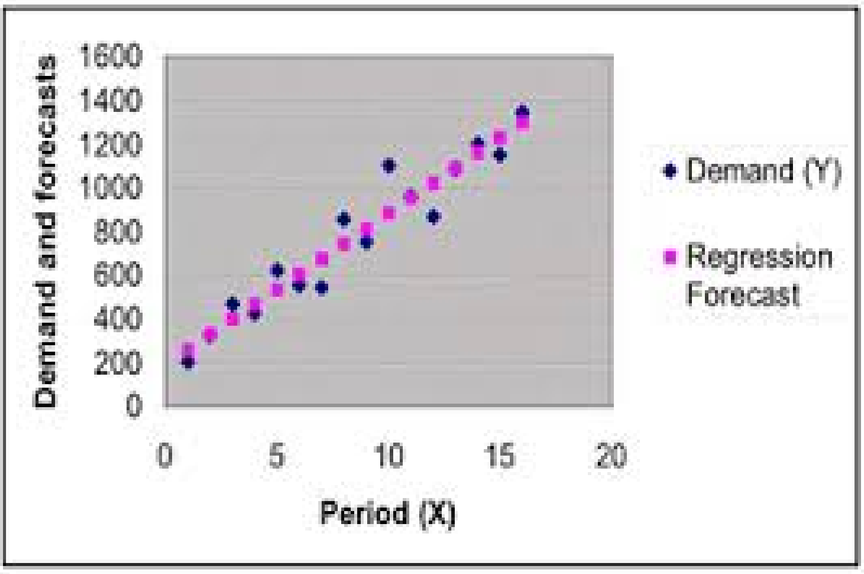

Fig 1. Typical Forecast Regression Model (Rexhausen, Pibernik, & Kaiser, 2012)

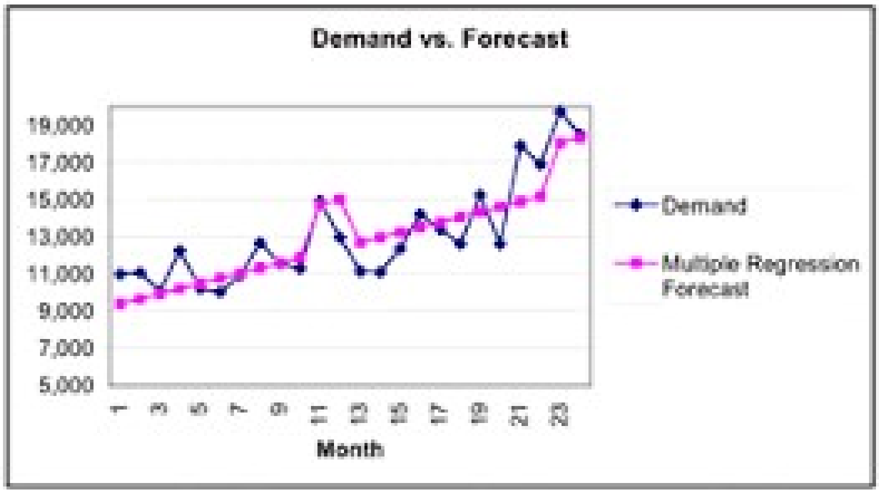

Fig 2. Typical Forecast Multiple Regression Model (Rexhausen, Pibernik, & Kaiser, 2012)

CONCLUSION

Unpredictability is a phenomenon that most businesses try to avoid since it may weigh heavily on its operations. Given this, the process of demand forecasting has grown in relevance as companies are increasingly applying techniques to forecast demand so as to plan for sales (Beutel & Minner, 2012). Although a range of techniques exists in literature as shown, it is difficult to find the one that assures the accuracy of the forecasts. It is so since most of them only take into consideration the historical sales of a company to make predictions. However, a few models exist that integrate other variables such as promotional features in addition to the historical sales. The study revealed that the CHAN4CAST model is the most suitable as it integrates historical sales information and promotional information of a company and the same features for other influential products. Influential products, in this context, refer to the products sold by competitors that potentially affect the sales of a company. However, further studies need to be conducted on feasible models that can be easy for use by businesses while at the same time guarantee accuracy

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