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DEMAND FORECASTING FOR PRODUCTION PLANNING IN A FOOD COMPANY

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ABSTRACT

The food and beverage industry is one of the most important sectors of the Brazilian economy, with a significant participation in GDP index. The Brazilian economy has been showing a relative stability in the last decades, which takes the sales demand to be more predictable. Due to this scenario of economic stability, the companies has been worried about investing in planning their operations, making use, mainly, of forecasting methods in order to become more competitive in the market. In the case of food industry, the seasonal and the short perishability factors are a limitation to the maintenance of stocks, requiring a forecast with a high accuracy level. The present work consists in applying methods to forecast the demand for products of a food industry, which directs its sales to the food service market, in order to base the short to medium term production planning. Posteriorly, the forecasts will be evaluated using the error measure MAPE and compared to the demand currently considered by the company. The proposed methods feature a reduction of the error approximately 5%.

Keywords: demand forecasting, production planning, exponential smoothing.

INTRODUCTION

The supply chain activities planning and control depends of accurate estimates of the volumes of products and services to be processed and the estimates come as forecasts (Ballou, 2007). One of the biggest challenges of food and beverage manufacturers is adjust the production and the stocks to minimize the loss of products due to its short perishability. Time series analysis is very important in a wide range of applications, especially when it comes to forecasting, and it encloses many different forecasting models. However, it is necessary to determine which model best suits each situation (de Oliveira Silva *et al.* 2014).

There are countless models to develop forecasts presentedin the bibliography. From market research to the most complexmethods computational. The reference (Ballou, 2007) presents the three main groups of these methods, they are: qualitative, historicalprojections and causal. Depending on the series and the desiredtime to be forecasted it is possible to choose a technique thatbest fits. Besides choosing the best technique, the forecasting tobe generated by the model chosen should be as close to real aspossible (Junior and Filho, 2012). In other words, the errors of forecasting should beminimized, so the production managers plan the production inattention to the market and minimizing the costs.

The demand forecasting methods can be based in mathematical models that use historical data or in qualitative methods, planned according to the administrative experience and customers reviews. They can also be based in a combination of both quantitative and qualitative methods (Lewis, 1997).

This study aims to analyze and forecast the sales demand in order to improve the short to medium term production planning. For minimize the group of analysis, an ABC ranking was utilized to determine that products have bigger importance in demand and in sales.

Exponential Smoothing Models

The exponential smoothing models are based on smoothing the past data of a time series to predict the future. Among the main advantages of this model are the simplicity and the low cost of application. They are recommended, mainly, when the time horizon is short.

Exponential methods have also been applied in other fields, as in the investigation of exponential random geometric graphs (RGGs) process models. The RGGs characterizes many randomly deployed networks, such as wireless sensor networks (Shang, 2009).

In the following, the main exponential smoothing methods will be presented: The simple exponential smoothing method, the Holt's method and the Holt-Winters method.

Simple Exponential Smoothing

According to (Krajewski *et al.* 2012), the simple exponential smoothing is a sophisticated method of weighted moving average. In this method, each new forecast is gotten from the previous forecast, increased by the error in the previous forecast which is corrected by a smoothing coefficient.

This method can be applied in forecasting stable demand series, those who oscillate around a constant basis. According to (Krajewski *et al.* 2012), the smoothing coefficient (α) balances the forecast sensitivity to the demand changes and the forecast stability. This coefficient has to be contained in the interval [0;1]. The greater is the value ofα, the faster the model will react to variations in the real demand, because the adjustment will be more aggressive compared to the forecast error made in the previous period. Otherwise, the smaller is the value of α, the less aggressive the adjustment will be, in other words, the forecasts will be more smoothed by the previous forecasts and the model will take more time to assume the changes in the time series data pattern.

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Holt's Method - Exponential Smoothing with Trend Adjustment

The exponential smoothing with trend adjustment sometimes referred as double exponential smoothing or Holt's Method, is a variation of the simple exponential smoothing method and is used to treat seasonal demand with trend (Alexandrov *et al.* 2012).

This method uses two smoothing coefficients, α andβ (with values between 0 and 1) and consists in making the forecast based in two factors: the forecast of the average using the exponential smoothing and a trend exponential estimative.

Holt-Winters Method –Exponential Smoothing with Trend and Seasonal Adjustment

According to (Giacon and Mesquita, 2011), the Holt-Winters method incorporates not only trend, but also a seasonal component. The seasonal demand data are characterized by the occurrence of cyclic patterns of variation that repeat in constant time intervals (Tratar, 2015).

The Holt-Winters method is based in three smoothing equations that are associated to each one of the series pattern components: level, trend and seasonality (Christo *et al.* 2013).

For series where the range of the seasonal cycle keeps constant over time (additive seasonality), the forecast can be calculated through Eq. 1 to 4 (Hyndman *et al.* 2005):

$$M_t = \alpha(D_t - S_t - s) + (1-\alpha)(M_t - 1 + T_t - 1) \quad (1)$$

$$T_t = \beta(M_t - M - 1) + (1-\beta)\,Tt - 1 \quad (2)$$

$$S_t = \gamma(D_t - M_t) + (1-\gamma)\,S_t - s \quad (3)$$

$$\hat{Z}_{t+k} = M_t + kT_t + S_{t-s-k} \quad (4)$$

D_t = demand for the period t;
M_t = forecast of the level for the period t;
T_t= forecast of the trend for the period t;
S_t = seasonal índex for the period t;
α= smoothing coefficient for mean (0 < α < 1);
β= smoothing coefficient for trend (0 < β < 1);
γ = smoothing coefficient for seasonality (0 < γ < 1);
s = a complete seasonal period (Ex: s = 12 when having monthly data and annual seasonality);
$\hat{Z}_{t+k}$= demand forecasting for the next *k* periods ahead.

For series where the range of the seasonal cycle varies over time (multiplicative seasonality), the forecast can be calculated through Eq. 5 to 8:

$$M_t = \alpha\frac{D_t}{S_{t-s}} + (1-\alpha)(M_{t-1} + T_{t-1}) \quad (5)$$

$$T_t = \beta(M_t - M_{t-1}) + (1-\beta)\cdot T_{t-1} \quad (6)$$

$$S_t = \gamma\frac{D_t}{M_t} + (1-\gamma)\,S_{t-s} \quad (7)$$

$$\hat{Z}_{t+k} = (M_t + kT_t)\,S_{t-s-k} \quad (8)$$

D_t = demand for the period t;
M_t = forecast of the level for the period t;
T_t= forecast of the trend for the period t;
S_t = seasonal índex for the period t;
α= smoothing coefficient for mean (0 < α < 1);
β= smoothing coefficient for trend (0 < β < 1);
γ = smoothing coefficient for seasonality (0 < γ < 1);
s = a complete seasonal period (Ex: s = 12 when having monthly data and annual seasonality);
$\hat{Z}_{t+k}$= demand forecasting for the next *k* periods ahead.

The index values for level, trend and seasonality can be calculated through Eq. 9 to 11:

$$M_s = \frac{1}{s(D_1 + D_2 + \cdots + D_s)} \quad (9)$$

$$T_s = \frac{1}{s}\left[\frac{D_{s+1} - D_1}{s} + \frac{D_{s+2} - D_2}{s} + \cdots + \frac{D_{s+s} - D_s}{s}\right] \quad (10)$$

$$S_s = \frac{D_1}{M_s}, S_2 = \frac{D_2}{M_s}, \ldots, S_s = \frac{D_1}{M_s} \quad (11)$$

ABC Analysis

The ABC analysis is based on the Pareto's Principle, defined by the Italian economist Vilfredo Pareto, who says that the majoritarian values (80% of its value) of a particular group comes from a relatively short portion of its components (20 % of its quantity).

The most applied method to aggregate products is the ABC ranking that determines the importance of the product, relating demand and sales (Krajewski *et al.* 2012).

In this case, the products can be grouped into three categories:

- A Items – Represents 80% of the company sales and about 20% of the products sold. The demand forecast is made individually for each product from this category, however, it maybe manager interest the stratification of the time series according to the region, costumer or sealer;
- B Items - Represents 15% of the company sales and about 30% of products sold. As for the A category, the forecasting is made individually for each product from this category, however, it does not need stratification. If any stratification is made over the series correspondent to the A category, the statistical treatment of the series are the same.
- C Items– Represents 5% of the company sales and about 50% of the products sold. The demand forecast is made in an aggregated way for the products of this category.

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The most applied method to aggregate products is the ABC ranking that determines the importance of the product, in demand and in sales (Eksoz *et al.* 2014).

In this case, the products can be grouped into three categories as illustrated in the Figure-1.

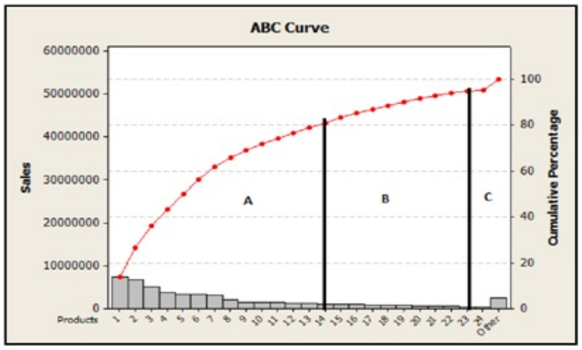

Figure-1. ABC curve (Source: Author).

The A items represents 80% of the company sales and about 20% of the products sold. The demand forecast is made individually for each product from this category, however, it may be manager interest the stratification of the time series according to the region, costumer or sealer. The B items represents 15% of the company sales and about 30% of products sold. As for the A category, the forecasting is made individually for each product from this category, however, it does not need stratification. If any stratification is made over the series correspondent to the A category, the statistical treatment of the series are the same. The C items represents 5% of the company sales and about 50% of the products sold. The demand forecast is made in an aggregated way for the products of this category (Schmit and Kaiser, 2006).

Case Study

The company to be analyzed in this case study is a food industry that directs its sales to the food service market. The midsize industry is located in Volta Redonda, Rio de Janeiro and focuses its production in pasta and sausage, composed of 6 different production lines that produces 49 different types of products and supply two restaurants chains and a pizzeria chain located all over Brazil.

For The ABC analysis, were considered the sales of all products from January 2012 to January 2014. This plot allows not only identify how much each product represents over the total sales, but also, determine the three product categories. Among all products from A category, the first two products of the ranking, that represent together 27% of the company sales in the considered period were chosen to be analyzed. The monthly sales of the selected products from January 2012 to January 2014 were plotted using the software Minitab®. The plots are shown in the following figures (Figure-2 and Figure-3).

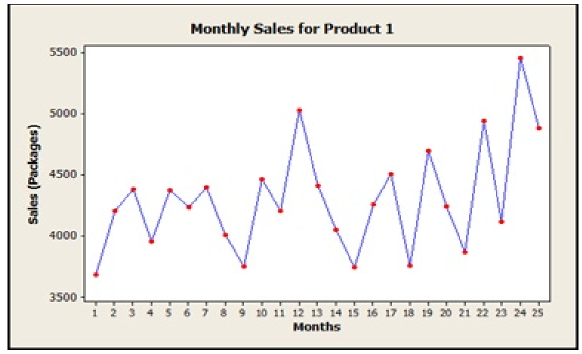

Figure-2. Monthly Sales of Product 1 (Source: Author).

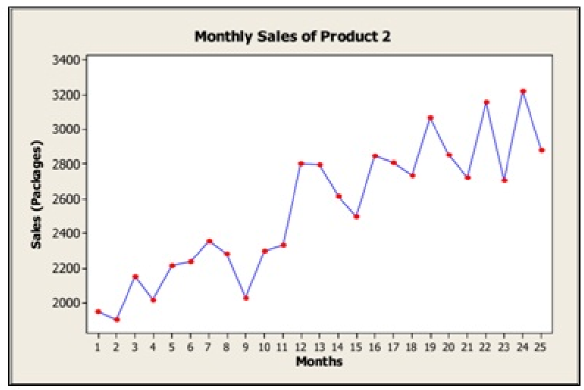

Figure-3. Monthly Sales of Product 2 (Source: Author).

During this period, the product 1 has shown seasonal pattern, despite its aleatory pattern in the first months. Most of time, cycles of 3 months can be observed, although this pattern is more marked in the last 10 months. We can also notice that the cycle range varies over time. In the last 7 months is possible to notice a sales increasing trend.

During the analyzed period, an increasing trend can be clearly observed in the sales of this product 2. A seasonal pattern with cycles from 3 to 4 months also can be observed, although this pattern is more marked in the last 10 months. The seasonal cycle range keeps constant as the time goes by.

From the analysis of the demand pattern through the graph (Figure-2), the most suitable method, for this product, is Multiplicative Holt-Winters Method, because this time series presents a marked trend in the last 7 months and also a seasonal pattern, which amplitude varies over time.

From the analysis of the demand pattern through the graph (Figure-3), the most suitable method, for this product, is the Additive Holt-Winters Method, because this time series presents not only trend, but also a seasonal pattern. The seasonal cycle range remains constant over time.

The respective Holt-Winters Methods were applied using MS-Excel®. The index values of M_0, T_0, e S_0 were settled through the Eq. 5 to 7 and a seasonal cycle of 3 periods were considered in both cases. To determine the optimal values for the α, β and γ coefficients the Solver tool of the software Excel® was used (Hyndman *et al.* 2008).

The nonlinear programming problem solved by Solver aims to determine the values of α, β and γ that minimize the value of MAPE (Mean Absolute Percent Error), with the restrictions that α, β and γ must be contained in the interval [0,1] (de Oliveira Silva *et al.* 2014).

After setting the Solver parameters, and ask for solving the problem, the tool provides the optimal values for the smoothing coefficients.

The optimal values of α, β and γ found for product 1 were:

$$\alpha = 0{,}03 \quad \beta = 1{,}00 \quad \gamma = 0{,}18$$

The optimal values of α, β and γ found for product 2 were:

$$\alpha = 0{,}00 \quad \beta = 0{,}16 \quad \gamma = 0{,}35$$

Considering the smoothing coefficients found and a seasonal cycle of 3 periods, the Minitab® software was used to forecast the demand of the product for the months of February, March and April 2014 using the Multiplicative Holt-Winters Method for product 1 and the Additive Holt-Winters Method for product 2, with a confidence level of 95%.

Considering the forecasts obtained for the months of February, March and April 2014 and the real sales in this period, a Mean Absolute Percent Error (MAPE) of 1,38% was obtained for product 1 and of 3,14% for the product 2.

To verify the performance of the obtained forecast and the effectiveness of the proposed methods over the method currently used by the company to forecast de demand, a comparison was made using the value of MAPE (Table-1).

Table-1. Comparison of the results.

	Product 1	Product 2
Proposed Method MAPE	1,38	3,14
Current Method MAPE	7,26	8,18

Through the MAPE values obtained with the proposed methods, it can be concluded that the applying of these methods in the respective time series offer satisfactory results due to the significant reduction of the error approximately 5%when compared to the current method.

CONCLUSIONS

Demand forecasts is, with no doubt, the basis for developing an efficient supply chain. The supply chain planning and control depends of accurate estimates of the volumes of products and services to be processed to satisfy customer's needs.

It can be concluded that the Holt-Winters method, which was applied in the time series analyzed in this work, showed its effectiveness for forecasting demand of products that presents trend and seasonality patterns in sales history. The use of the tool Solver of Excel® made it possible to obtain smoothing coefficients in a simple way, working as an effective alternative for obtaining them even though when the access to robust computational packages is not possible.

The method applied in this work showed its simplicity and accessibility due to the low cost and easiness of application. By having these characteristics, this method can be used by small and medium-sized companies, where is not possible to make huge investments in planning their operations.

The food products have a factor that limits the maintenance of stocks, the short perishability. These products have a period in which they keep their characteristics and should be consumed before being considered unsuitable for consuming. Thus, it is suggested for future works that the short perishability of products must be taken into account when evaluating the results obtained by the quantitative methods. To make possible not only plan the production to satisfy the forecasted demand, but also contribute to minimize the loss of products due to its short perishability and consequently, improving the profitability of the company.

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