DEMAND FORECASTING: A CASE STUDY IN METALLURGICAL SECTOR WITH TIME SERIES DECOMPOSITION

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ABSTRACT

This research is a case study of a company in the American metallurgical sector, manufacturer of more than a thousand and six hundred models of industrial vibrators, for which is estimated the demand for six products of the vibration pistons line, using a technique that combines moving average, exponential smooth and time series. The demand forecasting model proposed in this work improves the forecast in the sense of reliability and accuracy of the data generated by it. Comparing with other forecasting models, through evaluation index that are used in the literature, make a confirmation of the forecast improvement.

KEYWORDS. Demand forecasting; Time series; Moving Average.

MAIN AREAS: Statistics.

1. Introduction

One of the first steps to make any decisions for the planning of a company are the specific forecast data to provide adequate information for decision making. Appropriate forecasting models create a higher quality result, allowing better decisions [Hopp and Spearman 2008]. This study takes into account the importance of understanding the current demand data in an effort to make the best choice of a demand forecasting model.

There are many methods that can be used for forecasting. The methods that are relevant to the situation considered depend on the study objectives and the conditions facing the company (such as the available types of data). Often, there is no single best method. In fact, it is better to use different methods and match the forecasts [The International Institute of Forecasters 2015]. The main goal is not to identify the best forecasting method, but combine forecasts, if appropriate, to use more than one method for the data series studied. It is suggested to select forecasting methods that seem relevant, make predictions with each one, and then calculate the average forecast [Armstrong 2001]. This procedure improves the forecasts and have reduced error by 12%, also shows that make even greater gains in precision by combining forecasts using different methods and based on different data [Graefe et. al. 2012].

However, it may still be interesting to know which method is best. An approach that can be taken is the same as the accuracy of researchers, which is a kind of drive tournament or competition between alternative forecast methods. To do this successfully, it is necessary to meet three conditions: first one is to compare methods based on previous performance (forecast accuracy, not how well they fit the historical data); second one is to compare the predictions with the well accepted forecasting methods; and the last one is to use an appropriate sample for the forecasts [Collopy-et. al. 1994].

Having understood the current questions for choosing a suitable prediction method for a company, this research aims to develop the forecasting method called Decomposition method. The Decomposition method is a sort of mixture of more common methods of demand forecasting. In order to show how applying methodology from different forecasting methods in a single method could lead to better accuracy, this research also makes a comparison with the proposed forecasting method and two other more simple and common methods: moving average and exponential smoothing.

This research presents the case study of an American company in the mechanical engineering sector [Justiniano 2015]. Due to confidentiality requested, the company's name will not be given, but it is registered that the company is manufacturer of over a thousand and six hundred models of industrial vibrators for the American market. The company provided the past demand data of its products in the four-year period (2011 to 2014) and need the forecasting demand of several products. One of these products, called here Product G, is used for application of forecasting methods.

The remainder of this paper is organized as follows: Section 2 provides basic nomenclature and theory. Section 3 introduces the Decomposition method. Section 4 presents the case study, showing the results and comparison with method of moving average and exponential smoothing. Conclusions are presented in Section 5.

2. Basic Nomenclature and Notation

Here they are defined here some variables and basic notations considered in the text:

1) The notation used for a *Time Series* is:

$$\{A(t)\}_{t=1}^{N} \tag{1}$$

where $t\ (= 1,2, \ldots, N)$ is the time period and $A(t)$ is the t period demand.

2) The notation used for a *Forecast* is:

$$F(t) = f(t+\tau) \tag{2}$$

where $f(t+\tau)$ is demand forecast in the $(t+\tau)$ period and $\tau\ (= 1,2, \ldots)$ is a constant to generate future period.

3) The notation for the *Moving Average* approach is:

$$F(t) = \frac{\sum_{i=t-m+1}^{t} A(i)}{m} \tag{3}$$

where m is the order of the method, a user chosen parameter that represents the time t that it takes into account for the calculation of the forecast (the method memory).

4) The notation for *Exponential Smoothing* approach is:

$$F(t) = \alpha A(t) + (1-\alpha)F(t-1) \tag{4}$$

where α is a constant smoothing between 0 and 1, which can be chosen by the user or optimized for a better result of the forecast.

5) The notation for *Multiplicative (Additive) Model* of the decomposition method is:

$$A = T \times S \times C \times I \; (A = T + S + C + I) \tag{5}$$

where A is the observed value, T is the trend, S is the seasonality, C is the cycle and I are irregularities [Menezes 2007].

6) The notation for *Calendar Effect* is:

$$W_t = \frac{\text{Day number in the month t}}{Average\ number\ of\ days\ in\ a\ month} \tag{6}$$

where W_t is the weight of month's days variation relative to month t. The *Average number of days in a month* is the division of year's days (365) by the number of year's months (12), then 30.42 days per months. The *Day number in the month t* is exactly the value of the number of days in month t.

7) The notation for deviation is $e_t = f(t) - A(t)$ and for *Evaluation Measures* is

a) *MAD* for Mean Absolute Deviation (Gorard, 2014):

$$MAD = \frac{\sum_{t=1}^{n} |e_t|}{n} \tag{7}$$

b) *MSD* for Mean Square Deviation (Gorard, 2014):

$$MSD = \frac{\sum_{t=1}^{n} (e_t)^2}{n} \tag{8}$$

c) BIAS for the differences between actual data and forecasts [Hopp and Spearman 2008]:

$$\text{BIAS} = \frac{\sum_{t=1}^{n} e_t}{n} \tag{9}$$

3. Decomposition Method

The Decomposition method is a quantitative forecasting method consisting of mathematical models based on historical data of the company, that provide information on the variation in demand over a period of time [Fernandes and Anznello 2010]. The mathematical models used by quantitative methods are causal or temporal series. The causal links the response to a number of factors that determine it by a mathematical relationship, so needing a very careful analysis of possible factors, with an extensive database [Box et al. 1994]. However, the methods of time series, which is the case of the decomposition method, take into account numerical information of the past (time series) and assume the possibility that some aspects of past patterns are repeated in the future (they do not deal with the factors which promote the demand change).

The first step in analysis of time series is modeling study phenomenon, then describe the behavior of the series, make estimates and evaluate which of the factors influencing the behavior. Making analysis of time series by Decomposition method, it is possible to observe that a time series data can be influenced by four main components:

- *Trend*, which is the product demand behavior for a long period of time;
- *Cyclical variations*, which are fluctuations in the values of variable longer than a year that can follow the business cycle;
- *Seasonal variation*, which is the variation that occurs year after year with a duration less than one year, often in the same period and almost the same magnitude;
- *Irregular variation*, which is the one that does not follow a pattern, fluctuations not explained.

Decomposition method explains the possible influence of the components in time series by breaking down each of these components of the series, identifying how much this component are influencing the series and finally making a prediction [Wang et al. 2012].

Not all time series models feature all the factors listed above. Decomposition of time data will help identify which of these factors are acting in the dataset under study. An important point of the decomposition model is to decide how to relate all the components that are influencing the time-series data [Menezes 2007]. There are two options the additive model and the multiplicative model (see (5)). This study uses the multiplicative model, because the time series worked her suffers high variations and do not follow a steady pattern; i.e. there is a dependence of seasonality on the trend [Fávero et al. 2003].

3.1. Trend

The trend of a time series indicates the behavior of the data during a long-term (i.e., if it increases, decreases or remains stable, and which speed changes occur). Identify the trend allows the removal of this component of the study series, so it can get a better view of the other components that can interfere in the demand [Morrettin and Toloi 2004].

Obtaining the trend it can be done through moving average models, exponential smoothing or regression. The method for obtaining the trend used here is the regression, because it is the method that facilitates the result generation for the component trend and makes it easier to apply the forecasting model.

Here the trend is considered linear, given by the least square method, which consists of estimators that minimize the sum of squared residuals regression. This method was chose as an example but there are others method that cam be used to calculated the trend, it is detailed explained by Justiniano (2015).

$$T = a + b \times t \tag{10}$$

where T is the trend value, *t* is time, *b* is the slope of the line and *a* is the linear coefficient of the straight line. And the coefficients are calculating by:

$$b = \frac{n \times \sum_{i=1}^{n}(t_i \times y_i) - \sum_{i=1}^{n} t_i \times \sum_{i=1}^{n} y_i}{n \times \sum_{i=1}^{n}(t_i{}^2) - \left(\sum_{i=1}^{n} t_i\right)^2} \tag{11}$$

$$a = \frac{\sum_{i=1}^{n} y_i - b \times \sum_{i=1}^{n} t_i}{n} \tag{12}$$

where y_i is denoting $A(t_i)$, t_i is the period associated, and *n* is the number of periods of the series.

3.2. Seasonal Variation

Seasonality in a series corresponding to the increase and drop fluctuations that are repeated in a certain period of the year, month, week or day. This stage of Decomposition method, that is calculating the seasonal index, can be called *deseasonalizing* the series data.

The deseasonalizing removes the seasonal effects in the data analyzed. It helps don't make wrong inference about some increase or decrease over a period time. The method used to calculate the seasonal index is known as ratio to moving average approach. It shows how above or below the determined demand stands in comparison to the all year demand. This was calculated by following steps:

Step 1: Calculating the moving average monthly order, i.e. the number of seasonal period equal 12 (using the equation (3) with m = 12).

Step 2: Centralize moving average of order 12, this is done because the order of the moving average is an even number, then actual results that average appear between months and not in an exact month as required for the calculation of the index. Making centralization is possible to obtain the result of a month, to do this just need an average between the values above and below the month you want to get the index.

Step 3: Calculate seasonal indexes for each period. As the multiplicative model is considered here, to obtain the index simply divide the original values of the series by the centered moving averages, calculated in Step 2.

Step 4: Working with data for four years, you get more than one seasonal index for each month. So it is necessary arithmetic mean of the indexes of each month.

Step 5: Finally, the sum of all 12 indexes should be approximately 12 because it being used the multiplicative model. In the multiplicative model only the trend has the same units as time series data, the other components are all indexes.

In the case of the multiplicative model, if seasonal indexes are approximately equal to 1, then the seasonality hasn't significant effect on the series data, but if the indexes are different of 1 indicates that seasonality affects the time series [Menezes 2007].

3.3. Cyclical and Irregular Variations

Typically the cyclic and irregular variations are analyzed together. This is justified because these two components are part of the irregular behavior in time series. The cyclical variations are long-term fluctuations around the trend but do not have the exact frequency that characterizes the seasonal pattern [Bouzada 2012]. However the irregular variations are derived from random components, arising from unexplained situations.

These variations are not always easily visible. Some cases need data for a decade to observe this variation [Menezes 2007]. Nevertheless, for this case study these variations are taken into consideration to have a complete analysis of worked time series.

Obtaining cycles and irregularities is possible by removing the trend and seasonality of the initial series data. As it is used the multiplicative model of the Decomposition, forecasting method to removing the trend and seasonality it should the following steps:

Step 1: Deseasonalize the time series, consisting of dividing each series data by the seasonal index for the same period.

Step 2: Remove the trend, consisting of dividing the deseasonalized data by the trend obtained by simple regression.

Step 3: Smoothing the series, to facilitate the observation of cycles (to improve this observation a moving average may be applied. In this work, it was used moving average of order 3 - relation (3), with $m = 3$).

In Step 3, he aim is to calculate the cyclical index looking for a little bit more responsiveness and a little bit more graphic smoothness [Devcic 2008]. The order $m = 3$ is midway between responsiveness and smoothing, as it isn't possible to choose the maximum level for theses two points at the same time, you should choose a point where this value is equal to or close to it for both parties concerned.

In the multiplicative model to identify cycles in the series should be noted patterns, as the values of the cyclic variation index higher or lower than 1 for at least a period of one year, if the variation index does not differ much from 1 they do not influence the series so it can be ignored in the forecasting process [Menezes 2007].

3.4. Calendar Effect

Some months have 31 days, others have 30 and February may have 28 or 29 days, and some holydays varies from year to year, this can cause difficulties in planning. If sales of your business are much higher on the weekend, it can generate significant forecast error. Because this is that it takes into account the so-called Calendar Effect.

The calendar effect consists of an adjustment for the month length in days. If this adjustment on the variation in month length is not done, the effects may appear as a seasonal effect, which can not cause serious forecasting errors, but will certainly make difficult to interpret any seasonal patterns [Insight Central 2010].

This adjustment is easily calculated using equation (6). For months with 31 days:

$$W_{31} = \frac{31}{30.417} = 1.019 \tag{13}$$

For months with 30 days:

$$W_{30} = \frac{30}{30.417} = 0.986 \tag{14}$$

For the month of February with 28 and 29 days:

$$W_{28} = \frac{28}{30.417} = 0.920 \tag{15}$$

$$W_{29} = \frac{29}{30.417} = 0.953 \tag{16}$$

These rates found for each month are used in demand forecasting adjustment in order to consider the variation of days in each month and a it cam be achieved a more accurate prediction.

3.5. Recomposition

Done the decomposition process, the achievement of each of the index components that influence the studied time series, following the next steps:

Step 1: Calculate the trend by simply regression method, as explained in section 3.1;
Step 2: Deseasonalize, as explained in section 3.2;
Step 3: Get the cyclical and irregular variation, as explained in section 3.3;
then, they are computed the values of T, S, C and I, equation (5). Thus, it is possible to proceed to the recomposition process, the process of associating all the components that have influence in the time series by the model of Decomposition forecasting considered. So it can be made the forecast demand according to the next steps:

Step 1: Multiply the seasonal indices S (obtained in section 3.2) by trend T (obtained in section 3.1).

Step 2: Multiply the product of Step 1 by the cycle and irregularities rates, C and I (obtained in section 3.3).

Step 3: Multiply the calendar effect (explained in section 3.4), for each corresponding month, by the product of Step 2.

After recomposition made it gets the forecast data. It is important to note that to forecast is the future (demand of the future period, which has not given historical data as the basis for calculating the components - T, S, C and I), so it takes into account the future trend. Clarifying the whole recomposition process for this period is done by the same way. But in the process of decomposition (obtaining indexes), the calculation of the indexes of the trend and seasonality follows the regression equation made to obtain trend of the original series data. And for calculating the cyclical and irregular indexes is obtained from the simple regression made with smoothed graphic data (graphic made for calculating the cyclical and irregular indexes in periods that there is historical data). This procedure is done by not having the existence of actual data of the series for future periods.

4. Case Study

This study analyze data from the monthly demand of product Product G from a company (Table 1), over a period of 4 years (2011/02 – 2014/11; a total of 47 data in time series, Fig. 1).

TABLE I - DEMAND OF PRODUCT G - A(t)

Product Unit	YEARS			
MONTH	***2011***	***2012***	***2013***	***2014***
JANUARY	19	8	8	20
FEBRUARY	11	14	18	10
MARCH	18	8	49	25
APRIL	20	18	7	15
MAY	4	9	6	26
JUNE	13	39	12	20
JULY	19	16	11	24
AUGUST	17	12	25	20
SEPTEMBER	12	3	16	23
OCTOBER	12	3	19	25
NOVEMBER	7	19	15	17
DECEMBER	12	5	12	

Fig. 1 shows the behavior of the time series. Note that visually it is difficult to set a data behavior pattern and which factors interfering in the variations of the data.

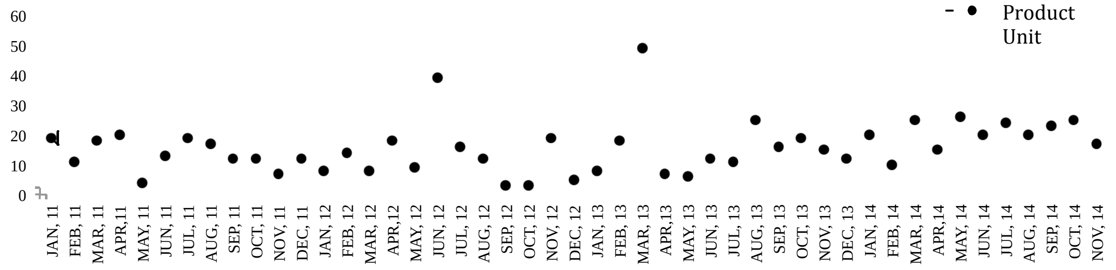

Fig.1. Demand of Product G by product unit.

4.1. Available Forecasters and Evaluation Measure

This study presents a forecasting method that works with several methodologies that come from other simple forecasting methods. In order to show that combining more than one forecasting methodology generates most accurate results, they are shown the results of predictions of more primary forecasting methods. The methods used are:

1) Decomposition Method
2) Moving Average of order 3 (relation (3), with m = 3)
3) Moving Average of order 6 (relation (3), with m = 6)
4) Exponential Smoothing (relation (4), with optimal α)

The choosing criterion for individual forecasters are: (i) easy methods to be implemented and understood, (ii) methods that work with time series and (iii) general methods that can be used for different series and that does not stick only to the study case. It is important to point that the Exponential Smoothing method is one of the most used methods to predict demand. Exponential Smoothing is the way used to discount the factors that interfere in historical data, where the most recent data has more weight than older data [Hopp and Spearman 2008].

At the same point of view, the method of Moving Average is one of the simplest methods and generic to apply. The moving average is based on the calculation of a simple average, but instead of using all previous data in the calculation of an average, for the prediction, it uses only some of the most recent data [Mentzer and Moon 2005]. It is important for this method to choose the order (m), because higher values of m will make a more stable model, but less responsive to changes in the forecasting process [Hopp and Spearman 2008]. So this study works with two different orders, 3 and 6.

The accuracy and measurement error of prediction are the common reasons for the calculation of forecast error, however for a better qualification of the forecast method is required more than one type of error measurement to supply all relevant information for the assessment beyond the forecast accuracy ([allström 2009]. In order to assess the demand forecasting model, they are presented three measures: Mean Absolute Deviation (MAD), Mean Square Deviation (MSD) and (BIAS), given in relations (7)-(9), respectively.

In this particular case it was applied a optimization of the Evaluation Measure indexes to obtain the optimal α. The optimization process is intended to minimize the forecast Evaluation Measure indexes from the following models:

$$Minimize\ Z = \frac{\sum_{t=1}^{n}|e_t|}{n}, \qquad Minimize\ Z = \frac{\sum_{t=1}^{n}(e_t)^2}{n}, \qquad Minimize\ Z = \frac{\sum_{t=1}^{n} e_t}{n},$$

$$subject\ to: \qquad F_{(t)} = \alpha A_{(t)} + (1-\alpha)F_{(t-1)}, \qquad t = 1, 2, 3, \dots, N; \quad 0 < \alpha < 0{,}5$$

4.2. Hypothesis Testing and Results

The hypothesis tested in this study is that the Decomposition method will be best evaluated by the evaluation measures of accuracy than the other methods that have been applied in the same time series. It is because the Decomposition method works together with various methodologies of forecasting. It was also taken into consideration the evaluation of the accuracy of methods with more than one forecast model so it can be obtained a more consistent result.

Fist are present the result of demand forecasting of the Product G by Exponential Smoothing method, Move Average (MA) of order 3 method and MA of order 6 method, with their respective relations, relation (4) and relation (3). Fig. 2, Fig. 3 and Fig. 4 show the graphics of each method mentioned, where the Black Series are the demand and the Red Series is the forecast. Attached Tables V, Tables VI and Tables VII show the forecast data for each of the methods.

- ***Exponential Smoothing Method:*** Optimal α is $\alpha = 0.0869$ and relation (4) is $F(t) = 0.0869A(t) + (0.91)F(t-1)$

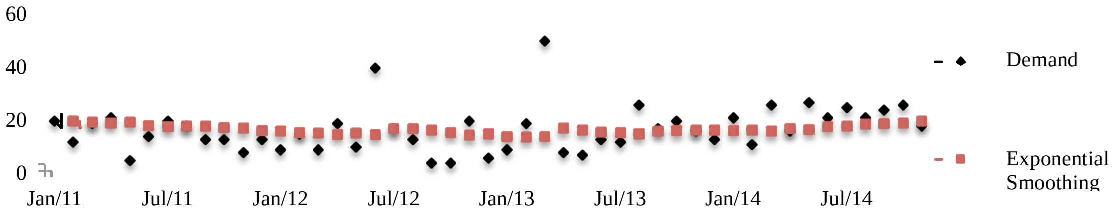

Fig. 2 Graphic of Forecasting by Exponential Smoothing of Product G

- ***MA 3 order Method:*** Relation (3) is $F(t) = \frac{[A(t-2)+A(t-1)+A(t)]}{3}$

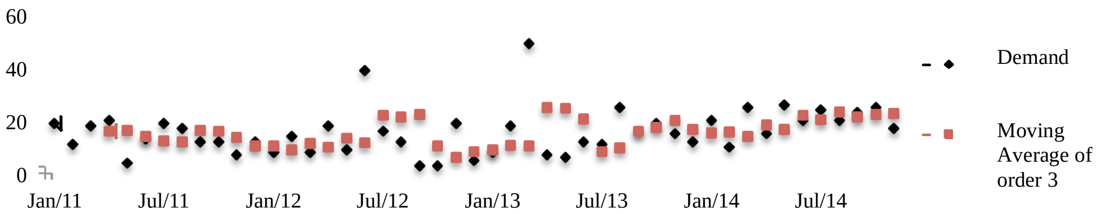

Fig. 3 Graphic of Forecasting by Move Average of Order 3 of Product G

- ***MA 6 order Method:*** Relation (3) is $F(t) = \frac{[A(t-5)+A(t-4)+A(t-3)+A(t-2)+A(t-1)+A(t)]}{6}$

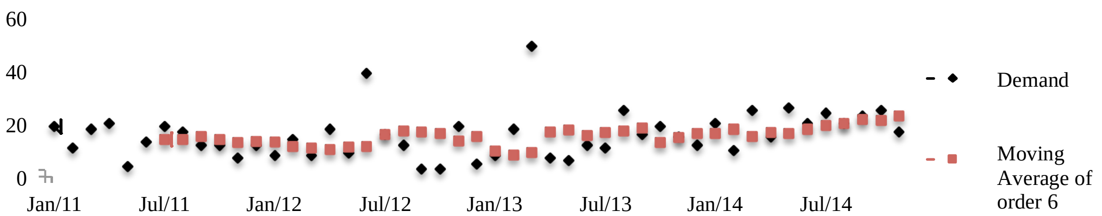

Fig. 4 Graphic of Forecasting by Move Average of Order 6 of Product G

Now is presented the result of demand forecasting of the Product G by Decomposition method. Starting with the process of decomposition that shows each component: trend (T), seasonal variation (S) and Cyclical and Irregular Variations (C and I). Finishing with the process of Recomposition that is the forecast itself.

- ***Trend (T):*** The relation (10) - $T = 11{,}637 + 0{,}173t$ (see attached Tables VIII for trend equation data).

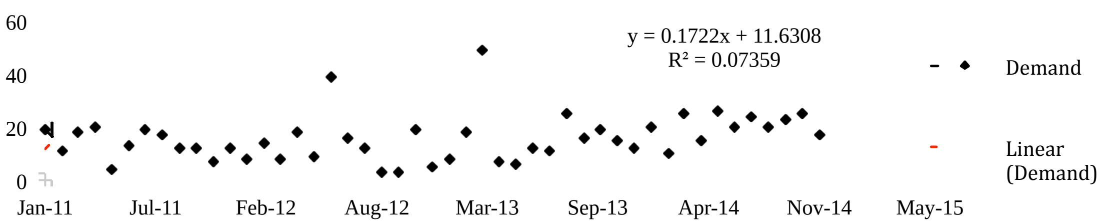

Fig.5. Trend Demand of Product G by simple regression.

- ***Seasonal variation (S):***
  Step 1 - $Sa = \frac{[A(t-11)+A(t-10)+\ldots+A(t-1)+A(t)]}{12}$
  Step 2 - $Sc = \frac{[A(t-1)+A(t)]}{2}$, where $A(t)$ is a value of Sa.

Step 3 - $S' = \frac{A(t)}{Sc}$, where $A(t)$ in this case is a value of the original data series.
Step 4 - Calculating the S as shows in Table II.

TABLE II - COMPONENT S

Product Unit	YEARS				
MONTH	***2011***	***2012***	***2013***	***2014***	***SEASONAL INDEX***
JANUARY		0.5533	0.6174	1.0884	**0.7530**
FEBRUARY		0.9912	1.3542	0.5345	**0.9600**
MARCH		0.5908	3.4087	1.3304	**1.7766**
APRIL		1.4072	0.4492	0.7759	**0.8774**
MAY		0.6968	0.3731	1.3220	**0.7973**
JUNE		2.9714	0.7404	0.9949	**1.5689**
JULY	1.4385	1.2468	0.6471		**1.1108**
AUGUST	1.3204	0.9231	1.4563		**1.2333**
SEPTEMBER	0.9536	0.2017	1.0105		**0.7219**
OCTOBER	0.9931	0.1860	1.2527		**0.8106**
NOVEMBER	0.5734	1.2225	0.9184		**0.9048**
DECEMBER	0.8889	0.3499	0.6857		**0.6415**

- ***Cyclical and Irregular Variations (C and I):***
  Step 1 - $Deseasonalized\ (D) = \frac{A(t)}{S}$, where $A(t)$ is a value of the actual series data.
  Step 2 - $C\&I' = {}^{(D)}/_{T}$
  Step 3 - $C\&I = \frac{[A(t-2)+A(t-1)+A(t)]}{3}$, where in this case $A(t)$ is a value of $C\&I'$

TABLE III - COMPONENT C&I

Product Unit	YEARS				
MONTH	***2011***	***2012***	***2013***	***2014***	***2015***
JANUARY		1.0567	0.7749	1.0323	1.0313
FEBRUARY	1.3095	0.7071	1.1748	0.9383	1.0332
MARCH	1.2137	0.9271	1.1142	0.7543	1.0351
APRIL	1.0286	0.8393	0.8771	1.1447	1.0370
MAY	0.9687	1.2962	0.4642	1.1143	1.0389
JUNE	0.7961	1.1430	0.4971	1.1849	1.0408
JULY	1.0155	1.0997	0.7404	0.8849	1.0427
AUGUST	1.2177	0.6281	1.0152	1.2075	1.0446
SEPTEMBER	1.1430	0.3860	1.2675	1.3549	1.0465
OCTOBER	0.9805	0.6197	1.1862	1.3910	1.0484
NOVEMBER	1.0154	0.6937	1.1093	1.0275	1.0503
DECEMBER	0.9012	0.8359	1.1542	1.0294	1.0522

- ***The process of Recomposition*** (see attached Tables IV for forecast data by Decomposition method):
  Step 1 - $F(t)'' = S \times T$
  Step 2 - $F(t)' = F(t)'' \times C\&I$
  Step 3 - $F(t) = F(t)' \times W_t$

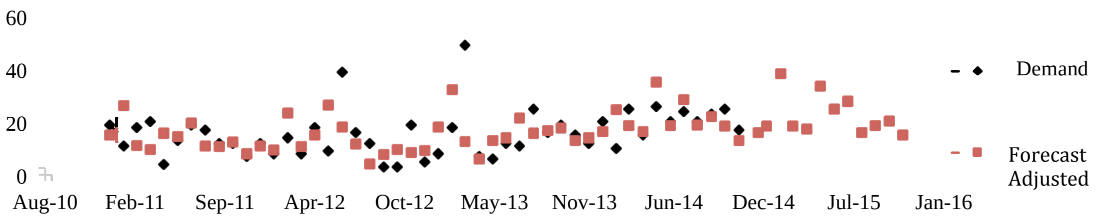

Fig. 6 Graphic of Forecasting by Decomposition method of Product G

Finally, for evaluation measure, the lower the value obtained for MAD and MSD, the best forecast fits to the original value of the time series. BIAS expresses if the forecasting is being over estimated (> 0) or underestimated (<0). This way it is observed in Table IV that the best method evaluated by evaluation measures is the Decomposition method.

TABLE IV - THE MOST ACCURATE PREDICTION METHOD

	EVALUATION MEASURE		
METHOD	***MAD***	***MSD***	***BIAS***
MOVE AVERAGE OF ORDER 3	7.08	110.36	-0.43
MOVE AVERAGE OF ORDER 6	6.58	95.08	-0.71
EXPONENTIAL SMOOTHING	5.74	79.10	-0.48
DCOMPOSITION	**4.78**	**39.26**	**0.23**

5. Conclusion

This study approaches the perspective of demand forecasting being strategic and production decisions of a company. The objective of this work is to show, through a case study that is possible to find a method that best fits (by providing a result of forecast with minor errors). Through a comparison with other demand forecasting methods the method developed in this study can be evaluated. In this way provides more accurate information for making business decisions. The study concludes that the Decomposition method using the multiplicative model was the method that provided the most accurate results, according to the evaluation measures used in the study.

The study explains in detail each step of the demand forecasting process for the Decomposition method, providing clarification of the forecasting methods used for comparative purposes and, finally, identifying each evaluation measure used in the study. Enable some observations and suggestions for future work in this area. The first observation is about the additive and multiplicative model, this work was done using the multiplicative model for demand forecasting method from the literature suggestions, however, it is appropriate to perform the analysis of the same data for the additive model and compare the results.

Additional comments on the study are: the demand forecast for Decomposition had the best evaluation Table IX); the study used the effect of the calendar as a way to improve the forecasting methodology, which took into account the effect of varying the amount of days in months in the monthly demand forecast data.

For future studies it is suggest use of more sophisticated method of forecasting, as Box-Jenkins method, to develop the process of comparison and find results even more precise.

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Attachment

TABLE V - FORECAST BY EXPONENTIAL SMOOTHING OF PRODUCT G

Product Unit	YEARS								
MONTH	***2011***	***2012***	***2013***	***2014***	***MONTH***	***2011***	***2012***	***2013***	***2014***
JANUARY		15.08	13.22	15.16	**JULY**	16.81	15.96	14.46	17.04
FEBRUARY	19.00	14.46	12.76	15.58	**AUGUST**	17.00	15.97	14.16	17.64
MARCH	18.30	14.42	13.22	15.10	**SEPTEMBER**	17.00	15.62	15.10	17.85
APRIL	18.28	13.86	16.33	15.96	**OCTOBER**	16.57	14.52	15.18	18.30
MAY	18.43	14.22	15.52	15.88	**NOVEMBER**	16.17	13.52	15.51	18.88
JUNE	17.17	13.77	14.69	16.76	**DECEMBER**	15.37	14.00	15.47	**18.72**

TABLE VI - FORECAST BY MOVE AVERAGE OF ORDER 3 OF PRODUCT G

Product Unit	YEARS								
MONTH	***2011***	***2012***	***2013***	***2014***	***MONTH***	***2011***	***2012***	***2013***	***2014***
JANUARY		10.33	9.00	15.33	**JULY**	12.33	22.00	8.33	20.33
FEBRUARY		9.00	10.67	15.67	**AUGUST**	12.00	21.33	9.67	23.33
MARCH		11.33	10.33	14.00	**SEPTEMBER**	16.33	22.33	16.00	21.33
APRIL	16.00	10.00	25.00	18.33	**OCTOBER**	16.00	10.33	17.33	22.33
MAY	16.33	13.33	24.67	16.67	**NOVEMBER**	13.67	6.00	20.00	22.67
JUNE	14.00	11.67	20.67	22.00	**DECEMBER**	10.33	8.33	16.67	**21.67**

TABLE VII - FORECAST BY MOVE AVERAGE OF ORDER 6 OF PRODUCT G

Product Unit	YEARS								
MONTH	***2011***	***2012***	***2013***	***2014***	***MONTH***	***2011***	***2012***	***2013***	***2014***
JANUARY		13.17	9.67	16.33	**JULY**	14.17	16.00	16.67	19.33
FEBRUARY		11.33	8.33	17.83	**AUGUST**	14.17	17.33	17.17	20.00
MARCH		10.83	9.33	15.33	**SEPTEMBER**	15.17	17.00	18.33	21.67
APRIL		10.17	17.00	16.83	**OCTOBER**	14.17	16.17	12.83	21.33
MAY		11.17	17.67	16.17	**NOVEMBER**	12.83	13.67	14.83	23.00
JUNE		11.50	15.50	18.00	**DECEMBER**	13.33	15.33	16.33	**21.50**

TABLE VIII - COMPONENT T

Product Unit	YEARS										
MONTH	***2011***	***2012***	***2013***	***2014***	***2015***	***MONTH***	***2011***	***2012***	***2013***	***2014***	***2015***
JANUARY	11.80	13.87	15.94	18.00	20.07	**JULY**	12.80	14.90	16.97	19.04	21.11
FEBRUARY	11.98	14.04	16.11	18.18	20.25	**AUGUST**	13.01	15.08	17.14	19.21	21.28
MARCH	12.15	14.22	16.28	18.35	20.42	**SEPTEMBER**	13.18	15.25	17.32	19.38	21.45
APRIL	12.32	14.39	16.46	18.52	20.59	**OCTOBER**	13.35	15.42	17.49	19.56	21.62
MAY	12.49	14.56	16.63	18.69	20.76	**NOVEMBER**	13.53	15.59	17.66	19.73	21.79
JUNE	12.66	14.73	16.79	18.87	20.93	**DECEMBER**	13.69	15.77	17.83	19.90	21.97

TABLE IV - FORECASTING BY DECOMPOSITION METHOD OF PRODUCT G

Product Unit	YEARS										
MONTH	***2011***	***2012***	***2013***	***2014***	***2015***	***MONTH***	***2011***	***2012***	***2013***	***2014***	***2015***
JANUARY		11.04	9.30	13.99	**15.89**	**JULY**	14.48	18.21	13.96	18.71	**24.91**
FEBRUARY	15.05	9.53	18.17	16.37	**18.49**	**AUGUST**	19.54	11.68	21.46	28.61	**27.94**
MARCH	26.19	23.41	32.23	24.59	**38.27**	**SEPTEMBER**	10.88	4.25	15.84	18.96	**15.99**
APRIL	11.12	10.59	12.66	18.60	**18.48**	**OCTOBER**	10.61	7.75	16.82	22.05	**18.73**
MAY	9.65	15.04	6.15	16.61	**17.53**	**NOVEMBER**	12.43	9.79	17.72	18.34	**20.43**
JUNE	15.82	26.42	13.10	35.08	**33.72**	**DECEMBER**	7.92	8.45	13.20	**13.14**	**15.11**