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USE OF FORECASTING TECHNIQUES TO ESTIMATE DEMAND IN SMALL AND MEDIUM-SIZED COMPANIES IN THE TEXTILE SECTOR

M. Teresa Ramírez-Ceballos[1], Roberto Baeza-Serrato*[2] & J. Jovani Cardiel-Ortega[3]
[1]Centro de Innovación Aplicada en Tecnologías Competitivas (CIATEC, A.C.), León, Guanajuato, México
*[2]Universidad de Guanajuato, DEM, Yuriria, Guanajuato, México
[3]Instituto Tecnológico Superior de Irapuato, Irapuato, Guanajuato, México

ABSTRACT

The aim of this article is to present a comparative analysis of statistical techniques to forecast the demand of clothing. Techniques were validated in a textile company producing knitted garments located in the south of the Mexican state of Guanajuato. A time series was analyzed to identify cyclicity, trends, seasonality, and random variations. Moving average, weighted moving average, exponential smoothing, Holt's method, and Winter's method were applied to demand forecasting. Model performance was tested by mean absolute deviation (MAD), mean squared error (MSE), and the R2 determination coefficient.The results proved simple exponential smoothing to be the best performing technique for demand forecasting. Forecasting techniques presented as spreadsheets will help decision makers to anticipate their clients' demand, respond promptly, and improve organizational aspects.The present study attempts to highlight the importance of providing small and medium-sized enterprises in the textile sector with engineering tools to improve their production and business processes by making informed decisions to enhance their competitive advantage.

Keywords: *demand forecast, smoothing techniques, SMEs, textile sector.*

I.   INTRODUCTION

Today's firms face a reality: they must anticipate, respond to, and react to growing market demands. In a fiercely competitive environment, a commercial strategy determines not only success, but also commercial survival (Fui-Hoon, Lee-Shang,andKuang, 2001). Companies ought to increase the efficiency and effectiveness of their business activities and address the need to reduce costs while improving performance. Therefore, managing performance throughout the company is a necessity if a competitive market position is to be maintained (Blasini and Leist, 2013). In this context, forecasting the demand is essential. A forecast is simply a prediction of what will take place in the future (Anderson *et al*., 2011).Campos (2014) defines demand forecasting as a quantitative estimation of the amount of products or services that will be required by the market in a certain period in the future. Demand forecasting is of utmost importance in planning the size of facilities, optimizing everyday operations, and managing available resources effectively.A key component here is the accurate prediction of time series (Bianchi *et al*., 2017) because tactical and operational decisions on production planning, inventory levels, transportation, and programming are based on the anticipation of the demand in the near future (Blackburn *et al*., 2015).

Due to their flexibility and innovation capabilities, small and medium-sized companies (SMEs) are fundamental to the dynamics and health of global economy. These companies play an important role as employment sources and supporting large-scale organizations (Su *et al*., 2016). In view of the intense international competition resulting from globalization, a firm's profits depend largely on the way in which it leverages internal and external resources (Moon *et al*., 2014). This is partly due to the recognition of the importance of SMEs for the economy in terms of the number of existing companies and the employment and added value they provide, and also due to the fact that SMEs' finances are considerably different from large companies' finances (Daskalakis, Balios, andDalla, 2017). In many European countries, SMEs account for almost 80% of the GDP and employment structure (Pletnev*et al*., 2016). According to SBA (2016) data, small companies represent 99.7% of employment sources in the United States. Similarly, 93.6% of manufacturing companies in Mexico are microbusinesses, whereas the second place is occupied by small companies (4.2 %) and the third place by medium-sized companies (1.5%), according to data by INEGI (2014).

At present, SMEs lack engineering tools to improve their production and business processes and conduct sound decision-making. Supporting these firms is essential if their inclusion in an increasingly competitive environment is to be accomplished. The present study contributes to the development and application of statistical techniques to forecast demand; these will support decision-making in a small company focused on the manufacturing and commercialization of knitted children's clothing in the south of Guanajuato (Mexico). In order to apply the statistical techniques, data on sales behavior was collected and analyzed, and the empirical process used by the company to forecast the demand of its products was analyzed. Statistical techniques were compared to determine the demand forecast model with the best performance.

The textile firm had being operating since 2011 at the time of the study. The plant uses Japanese-made flat knitting machines. Production process begins in the knitting area, where textile fibers are woven as canvases and then basted to facilitate ironing. Ironing is performed using steam ironing machines; this operation stabilizes the fibers and thecanvases undergo a certain natural shrinking so that cutting can take place. Garments are assembled in the sewingdepartment and final details are completed in the finishing department. Finally, garments are returned to the ironing department, where their final presentation is fixed and they are packed. The final product is sold to special types of clients, such as department stores, and is also distributed via retailers and sales points. The present study sought to determine future demand to optimize the use of resources and help the firm meet its objectives.

This article is structured as follows: The first section presents a review of the literature on forecasting techniques developed in different sectors, the second section presents the research method used in the present study, and the third section presents de development of the study. Results and conclusions are presented in the final section.

II.   LITERATURE REVIEW

This section presents the review of literature related to demand forecasting using time series techniques.
Campos (2014) studied demand forecasting and management practices employed by 366 Mexican companies, 52.3% of which were SMEs. A total of 96% of those companies used to take 12-month periods of historical data to conduct their forecasts; however, since such period is insufficient to provide information to identify seasonality or cyclicity, the author recommends using data periods from three to five years. Moving average models were reported to be the main forecasting technique by 62.63% of the firms because they are easy to apply. The present study used a five-year horizon and tested six different statistical methods in order to determine the best model to forecast demand for SMEs in the textile sector.

Ali *et al.* (2017) evaluated a strategy termed downstream demand inference, which is based on the simple moving average method and is applied to supply chains where information cannot be shared; the upstream or initial member of the chain infers consumer demand mathematically without sharing the information. The authors performed an analytic comparison and, experimenting with real sales data from an important German supermarket, their results demonstrated how the strategy decreases the mean squared error (MSE) of forecasts and inventory costs in the supply chain. For their part, Maçaira, Souza, and Oliveira (2015) applied an electricity consumption demand model based on type of residence and using simple exponential smoothing method, Holt's method and Pegels methodto the Brazilian Electricity System. Annual historical data from 1995 to 2013 was used by this study; in the time series, data showed an approximately linear growth trend, and a structural rupture in 2001. Parameters used for the Holt method were alpha = 1 and gamma = 0.329, and the obtained mean absolute percentage error (MAPE) was 3.916; as a conclusion, all techniques were adequate for historical adaptation with minimum error values. Sepúlveda*et al.* (2015) presented a forecasting model selection mechanism to assist with demand forecasts in supply chains. These authors applied their method to two Chilean companies, where they used different techniques and the MAPE criterion, and confirmed that choosing the method in advance adds accuracy to forecasts.

Lin *et al.* (2016) proposed the use of exponential smoothing to improve rental trends at bicycle stations in the Chinese city of Hangzhou. They selected 50 stations randomly and analyzed the three most pronounced rental patterns at a certain time of the day using mean average error (MAE) and mean relative error (MRE) values as prediction criteria, and the smoothing constant value used in their study was 0.1. Their results showed that these values can provide a basis to supply public bicycles in advance. Paraschiv, Tudor, and Petrariu (2015) used the Holt-Winters method to compare the contribution of national textile industries to water contamination among G20 member countries and forecasted the evolution of organic water pollutant total emissions for the next decade in two

Eastern Europe countries: Poland and Romania. The time horizon was from 1990 to 2007 and annual data were available; the forecasts indicated that both countries had a decreasing trend, and the accuracy of predictions was verified using an autocorrelation plot for the errors. Pal, Singh, and Dutta (2013) proposed a moving average model to predict route length in wireless networks with mobile nodes acting as hosts and routers for packet broadcasting; after comparing the AODV and DSR routing protocols, the authors found that AODV achieves the shortest route length. Using ECM, MAE, and MAPE as evaluation criteria, they concluded that the best order for this model is between periods 4 and 5 for different routes.

Most studies included in this literature review use one or two performance criteria; the present study considered three criteria to evaluate the different prediction models: mean absolute deviation (MAD), determination coefficient (R^2), and MSE. The studies presented in this literature review were used as guidelines for our own study to define the type of assessment for the time series, techniques and parameters to employ, and use of historical data. It should be highlighted that none of the reviewed studies focused on SMEs. As previously mentioned, the purpose of this study was to conduct a comparative analysis of statistical techniques applied to the forecast of clothing demand in a SME.

III. RESEARCH METHOD

Figure 1 illustrates the method used by this study to accomplish its goals. The demand of knitted children's garments was estimated in a series of eight stages.

Figure 1. Research method

STAGES	OBJECTIVES	PROCEDURES
Problem identification	To improve decision-making related to forecasts on the demand of knitwear children's garments	Analysis of the demand forecast process used
Theoretical basis	To review the state of the art of forecasting technique implementation	Scientific article database search
	To analyze the characteristics of the different forecasting techniques	Bibliography
Data collection	To know sales from previous years	Historical data on monthly sales
Analysis of information	To analyze the past behavior of the demand to identify trends, seasonality, cyclicity, and random variations	Time series plots Autocorrelation plot
Demand forecast	To develop statistical models to estimate the demand of knitted children's garments in the future	Moving average, weighted moving average, exponential smoothing, Holt's method, and Winter's method
Comparison of techniques	To determine the best statistical prediction model	Prediction criteria: mean absolute deviation (MAD), mean squared error (MSE), and determination coefficient R^2
Validation	To compare the results of the best model against real demand	Implementation in SME
Results	To analyze, discuss, and offer a conclusion based on our findings	Data evaluation

IV.   DEVELOPMENT

Not only are forecasts increasingly important, but also quantitative methods play an increasingly more significant role in forecasting procedures (Eppen*et al*., 2000). Time series forecasting refers to the estimation of future values based on previous observations at equidistant points in time. Statistical methods have been extensively used by the prediction research community over the past decades (Peng *et al*., 2015).

With time series techniques, data must be examined to detect patterns or behaviors and to verify four assumptions about the data: trend, seasonality, cyclicity, and random variations (Hanke andReitsch, 2006; Anderson *et al*., 2011). Unfortunately, no quantitative method has been singled out as the best technique. Data availability, the objectives of the study, and the nature of the studied phenomenon are important factors to determine the most adequate method (Lee, Song, andMjelde, 2008).

Problem identification
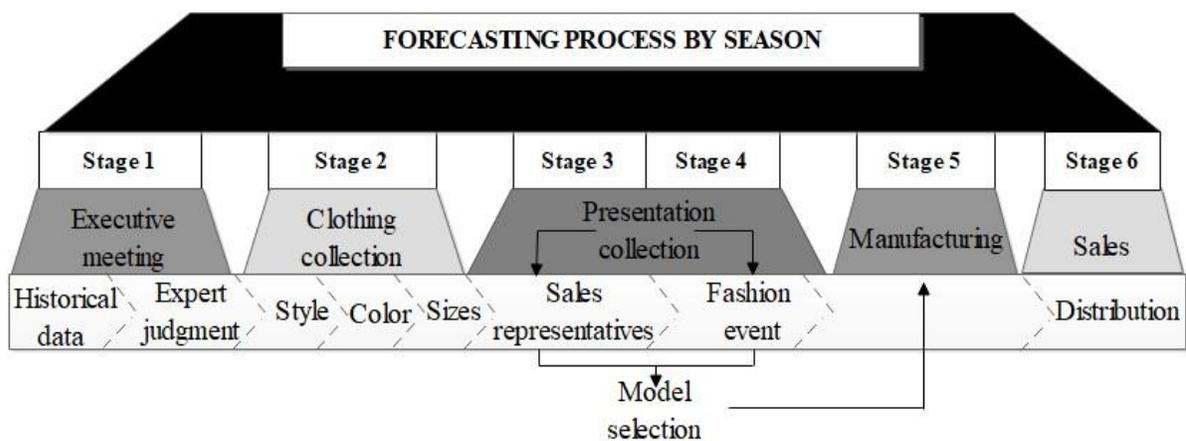
Figure 2. Forecasting process by season

The fashion supply chain is characterized by short product life cycles, volatility, and demand from unforeseen clients, extremely wide product variation, intense production work, and long supply processes (Guo and Wong, 2013). Figure 2 shows the empirical forecast process carried out for each season in the studied enterprise. Stage 1 consists in an executive meeting with the purpose of examining historical sales data, and clothing collection for the next season are defined based on experience. Model styles, colors, and sizes are defined in stage 2.The clothing collection is presented in two phases: in the first of these (Stage 3), sales representatives select the models to decide on production based on their intuition, and in the second phase (Stage 4), the company presents its products in an international fashion event, looking to grow its market and attract more clients. As a result of this event, decisions such as resupplying and cancelling or downsizing orders to respond to the demand are made in a very short time. Stage 5 is the part of the process when garments are manufactured. Finally, stage 6 consists in distribution to department stores, retailers, and company's sales points. The resulting analysis opens an area of opportunity for statistical techniques aimed at improving decisions made towards demand forecast. For most minor producers and clothing businesses, an anticipated calculation of the demand at the beginning of the season is necessary throughout the year. The success of a clothing retailer depends largely on the accuracy of pre-season forecasts, in which initial orders are based (Mostard, Teunter, and De Koster, 2011).

Data collection
Time horizon was from 2011, when the company opened, to 2015 (see Table 1). Monthly sales historical reports were gathered and data were screened based on the behavior of the demand during the peak season (fall-winter), from June to November.

Table 1. Sales history 2011 - 2015

	Sales (garments) / Month					
Years	June	July	August	September	October	November
2011	**1666**	**7426**	**2534**	**5422**	**1625**	**9028**
2012	**5124**	**5078**	**3721**	**10470**	**13116**	**8289**
2013	**5206**	**14121**	**15960**	**19227**	**9196**	**1443**
2014	**2421**	**5211**	**4148**	**15386**	**5722**	**3001**
2015	**9296**	**1881**	**7651**	**7545**	**3140**	**1206**

Analysis of information

The textile industry operates in an uncertain environment, where demand is affected by different factors such as the time of the year, short life cycles, high volatility, as well as factors related to the weather or the economy, among others (Sintec, 2012). A time series is defined as a sequence of observations ordered according to the time of the observation t, and registered continually or intermittently, as a rule, using the same interval between consecutive observations (Kharin, 2013). Figure 3 presents the time series showing the behavior of monthly sales. The fluctuation of observations is different each year, lacking a certain patterned behavior; the highest sales figure was during the month of September 2013, and the lowest in the month of November 2015.
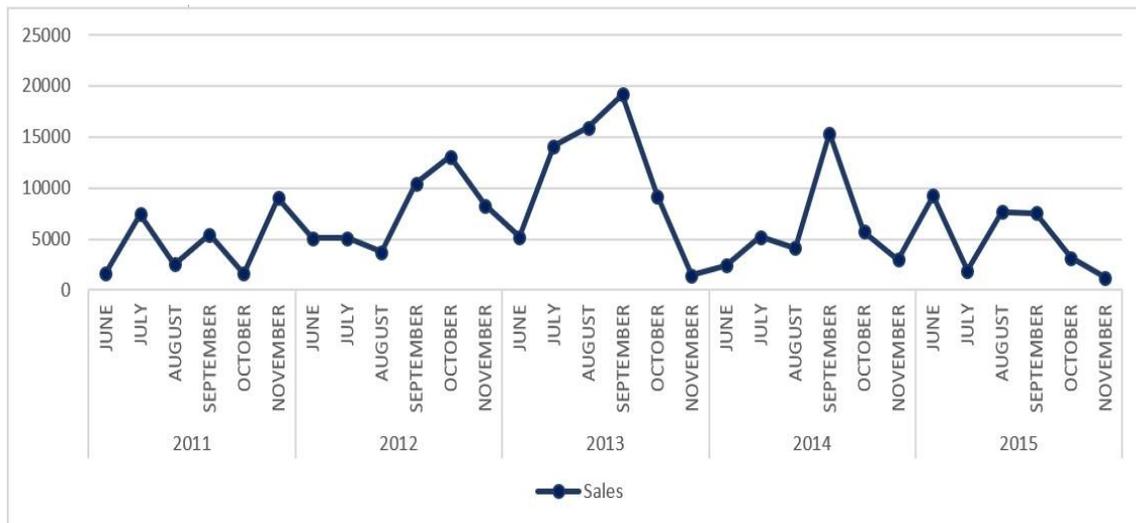
Figure 3. Sales time series

Identification of components

Time series variation hasfour different components. Over time, change can be linear or increase exponentially; long-term change (or the absence of change)is considered the trend of the time series, a first component of variation. The second component is cyclical variation. A normal business cycle is characterized by periods of prosperity followed by periods of recession, depression, and recovery; therefore, this component is the increase and reduction of a time series for periods of more than one year. The third component is seasonal variation. Many sales, production, and other types of series present fluctuations in different seasons, a pattern of change in a one-year time series; these fluctuations tend to repeat themselves each year. The fourth component is cyclical variation; after episodic fluctuations are eliminated, the remaining variation is called residual variation, which is unpredictable and due to randomness (Lind, Marchal, andWathen, 2015).

When a variable is measured over time, observations made at different moments are often associated or correlated; these are normally measured using the autocorrelation coefficient (Hanke and Wichern, 2012).
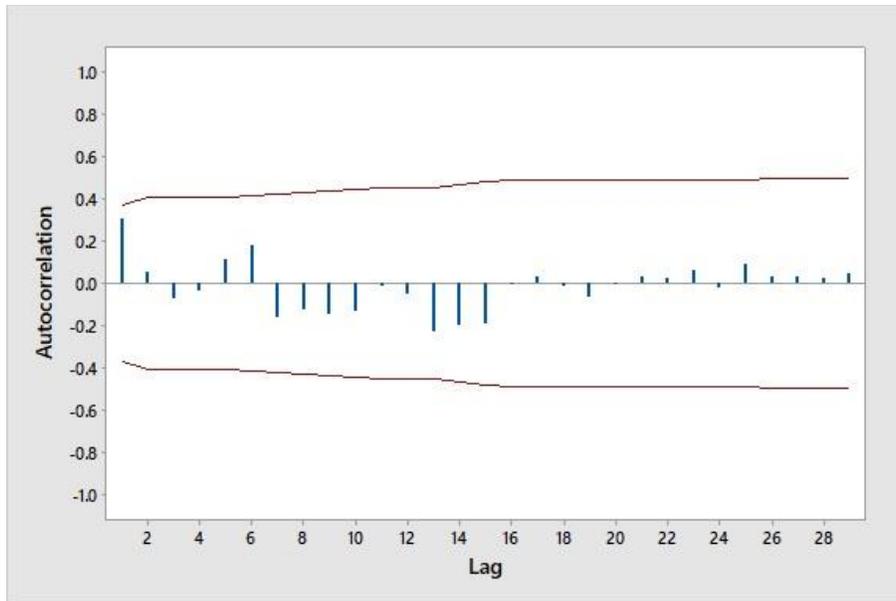
Figure 4. Autocorrelation plot

Figure 4 shows how autocorrelations are statistically close to zero, located within critical bands, which indicates that the data series can be considered random. Hanke and Wichern (2012) stated that, with the trend component, autocorrelation coefficients are usually large for many of the first time delays, and after that, as the number of delays increases, coefficients fall gradually to zero.In the plot, the first delays drift away from one, and subsequent coefficients vary and gradually fall to zero; as a result, the existence of the trend component is not clearly established, although a regression analysis can be performed in order to verify this component.

In a simple linear regression, the most uncomplicated deterministic mathematical relationship between two variables x and y is a linear relationship (see Equation 1). The set of pairs (x, y) for which the equation determines a straight line with a slope β_1 and the intersection with the y axis as β_0 is defined as:

$$Y = \beta_0 + \beta_1 x \tag{1}$$

More generally, the variable whose value is set by the experimenter and is represented with x is termed independent, predictive, or explanatory variable. The second variable is random; this random variable and its observed value are represented by Y and y, respectively, and it is referred to as the dependent or response variable (Devore, 2016).

The method of least squares was used;this method determines a regression equation by minimizing the sum of squared vertical distances between real and forecasted values of Y. The resulting regression line is known as the best-fitting line (Lind, Marchal, andWathen, 2015). The model obtained using this method is presented in equation 2.

$$Sales = 6942 - 6(month) \tag{2}$$

In this model, slope is negative and it shows a slightly decreasing trend, as shown in Figure 5. Trends are long-term movements over the time series, which in the present study was set to five years.

The seasonal component is represented in the time series; the factor attached to the time of the year has an effect on knitted garment sales because these garments are consumed when the weather is cold. The length of the seasonal component is six months.
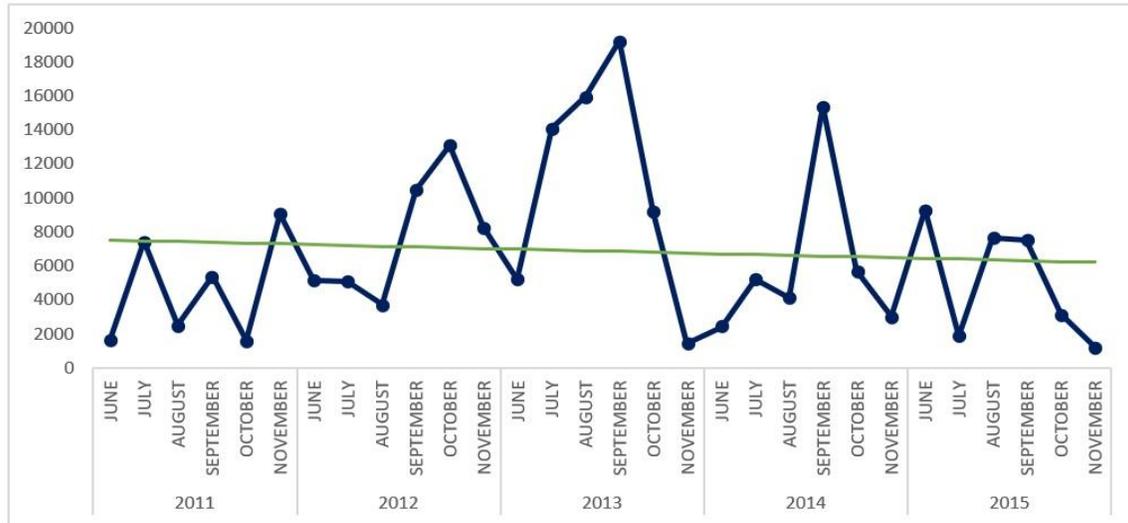
Figure 5. Trends plot

Demand forecast

Simple moving average (SMA)
The SMA forecasting method uses the arithmetic mean of the most recent observations. The most recent observation is included in each forecasting period, whereas the oldest is omitted (Ali *et al*., 2015).In mathematical terms:

$$\hat{y}_{t+1} = \frac{1}{n}(y_t + y_{t-1} + \cdots + y_{t-n+1}) \tag{3}$$

This study considered periods 2 to 8 (seven periods); prediction criteria were obtained to assess the accuracy of the fitted models for each period and each forecasting technique.

Table 2.Moving average results

Periods	MSE	MAD	R^2
n=2	28768646.25	4480.64	5.54
n=3	29984294.29	4398.48	1.54
n=4	30032536.32	4333.09	0.60
n=5	28320204.49	4292.26	0.49
n=6	26306190.32	4158.94	**2.36**
n=7	28867993.38	4608.58	0.28
n=8	30743288.88	4822.28	0.08

Table II compares performance in the different periods. Period 6 was found to have the lowest MSE and MAD values; therefore, the best moving average model is in this period (see Figure 6).
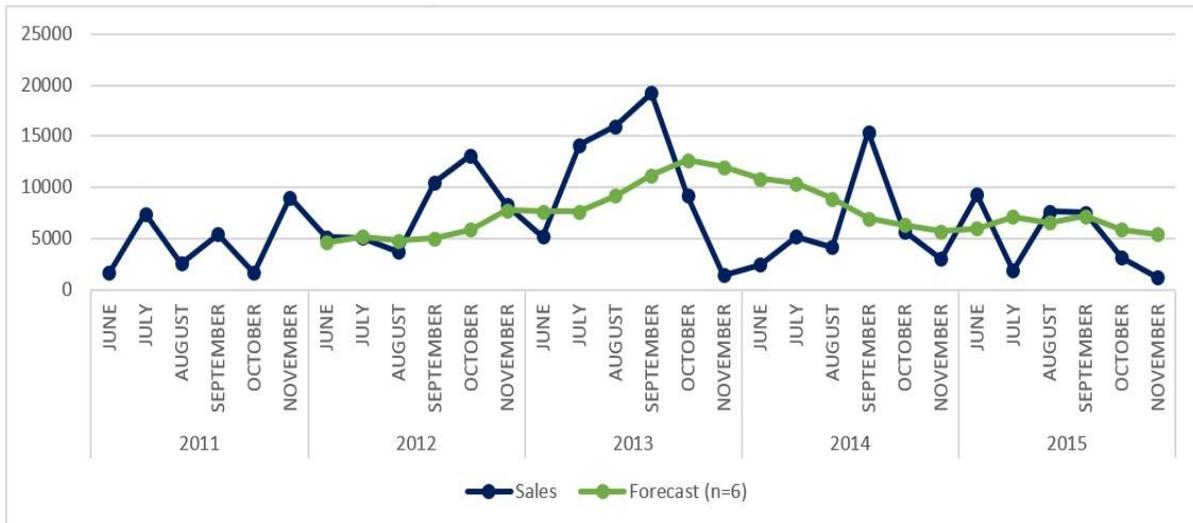
Figure 6. Moving average plot

Figure 7 shows a spreadsheet with the data for the best period according to the moving average technique. In this method, the actual sales of the first six months of operations (year 2011) are summed (Column J), and the result is divided by the number of periods (cell K16), which yields the first forecast (June 2012). Next, to calculate the forecast for July 2012 (cell M9), the last six sales figures (July 2011 to June 2012) are taken into account for the sum. This procedure is repeated to obtain sales forecasts for each month.

Figure 7. Moving average spreadsheet

Weighted moving average (WMA)
Recent data are more important than older data, which can be represented by using a weighted moving averageof*n* periods (Eppen*et al*., 2000).

$$\hat{y}_{t+1} = (\alpha_0 y_t + \alpha_1 y_{t-1} + \cdots + \alpha_n y_{t-n+1}) \tag{4}$$

$$\sum_{i=1}^{n} \alpha_i = 1 \qquad\qquad (5)$$

With this technique, time series data are weighted and recent sales are given more importance to smoothen fluctuations. Periods 2 to 9 were used.

Table 3. Weighted moving average results

Periods	MSE	MAD	R^2
n=2	**27515668.92**	**4466.62**	8.06
n=3	**27900001.11**	**4455.30**	**4.63**
n=4	**28418110.66**	**4355.49**	**2.79**
n=5	**28172817.95**	**4332.47**	**1.40**
n=6	27074151.85	4225.39	**2.28**
n=7	**28030794.31**	**4836.95**	**1.45**
n=8	**29297833.98**	**4671.51**	**0.59**
n=9	**30752263.38**	**4875.45**	**0.00**

Table III shows prediction criteria for each period; period 6 has the lowest MSE and MAD values. Demand forecast as resulting from this technique is shown in Figure 8.
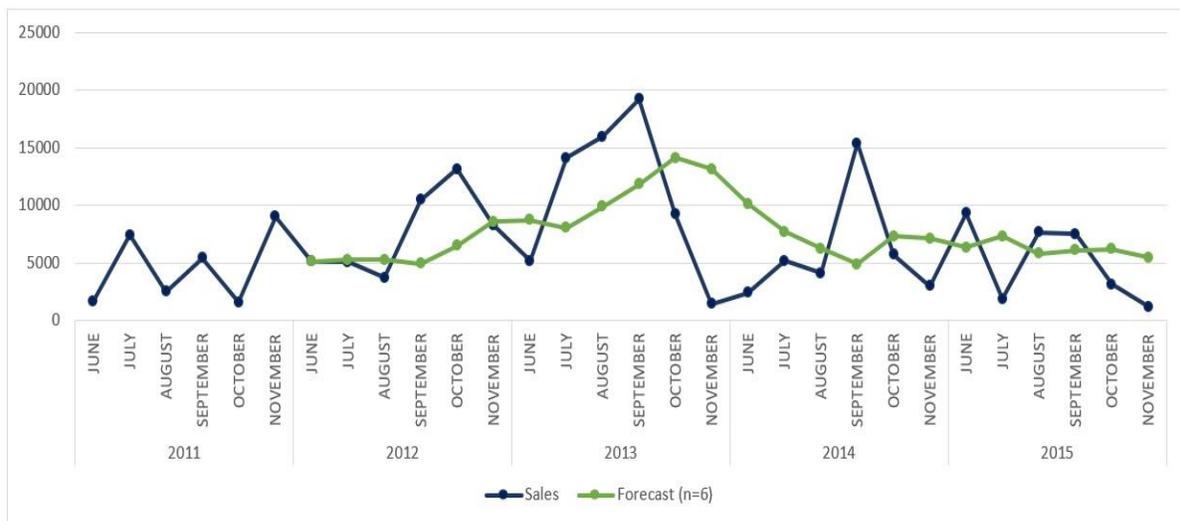
Figure 8. Weighted moving average plot

The spreadsheet with the data for the best period according to the weighted moving average method is shown in Figure 9. The different assigned weights are shown in cells K19 to K24. Recent items are given higher weights.The forecast for June 2012 is obtained by multiplying real monthly sales by the month's weight and dividing the result by the amount in the period (cell K18).

Figure 9. Weighted moving average calculation spreadsheet

Simple exponential smoothing (SES)
This method provides an average or smoothing of monthly sales figures in the time series by assigning decreasing exponential weights. There are two ways to initiate calculations in this technique; one of them is to take the value forecasted by another technique, and the other is to assign the previous value of data in the time series to the value to be forecasted. This study used the second option. The basic exponential smoothing model is:

$$F_{t+1} = \alpha y_t + (1 - \alpha)F_t \tag{6}$$

Hanke and Wichern (2012) point out that the smoothing constant described by α can be used as a weighting factor, and that it determines the degree to which the current observation has an effect on the forecast of the next observation. If steady predictions and smooth random variations are desired, a small value of α is required, whereas a prompt response should be targeted using a higher value of α. The Solver add-on for Excel was used as an optimal parameter for SES, Holt's, and Winter's techniques. A value of $\alpha = 0.335$ was obtained with the SES method. The best model according to the exponential smoothing technique is shown in Table IV and Figure 10.
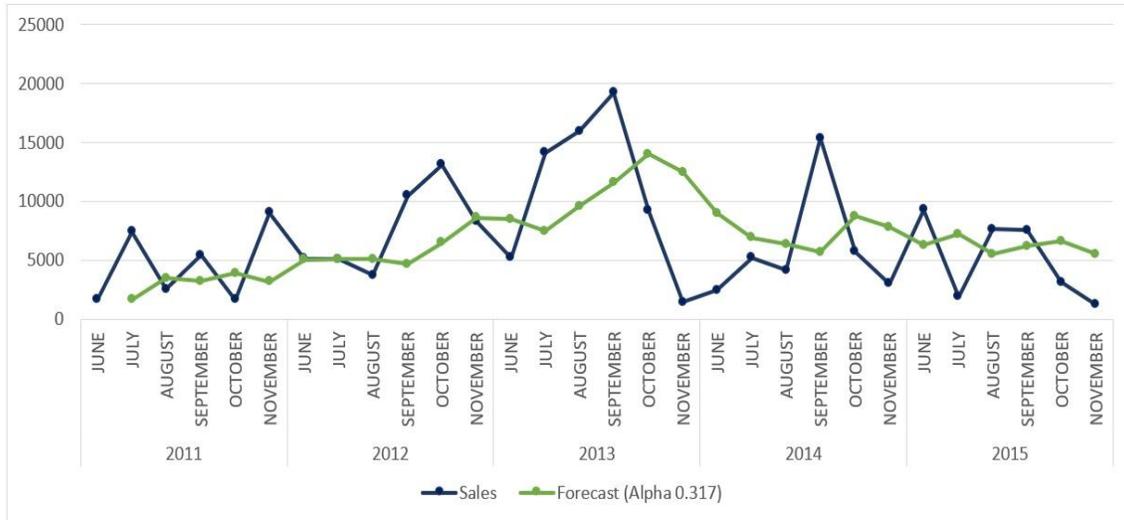
Figure 10. Exponential smoothing plot

Figure 11 presents a spreadsheet with the data for the exponential smoothing method. Calculations begin by taking the real sales figure for July 2011 (cell H6) as a forecast for the following month (cell I7). The average for August 2011 (cell I8) is obtained by multiplying the smoothing constant (cell I14) by the real sales figure of the previous month (cell H7) and adding the product of the previous forecast (cell I7) multiplied by the difference between 1 and the smoothing constant. This procedure is repeated to obtain forecasts for each month.

Figure 11. Exponential smoothing spreadsheet

Holt's method

Holt's trend projection method allows for the forecasting of up to k periods in the future. This model has two weighting parameters, α and β, both ranging from 0 to 1 (Paraschiv, Tudor, andPetrariu, 2015).

$$\hat{y}_{t+k} = L_t + kT_t \tag{7}$$

Where

$$L_t = \alpha y_t + (1 - \alpha)(L_t + T_{t-1}) \tag{8}$$

$$T_t = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1} \tag{9}$$

138

Holt's method includes an additional smoothing parameter, and its main difference with the exponential smoothing method is that it takes into account data on trends (FerbarandStrmčnik, 2016). The analysis of the sales time series identified a non-significant negative trend. Table 4 shows results obtained with the best combination of parameters α and β. Figure 12 shows the best model for this technique.
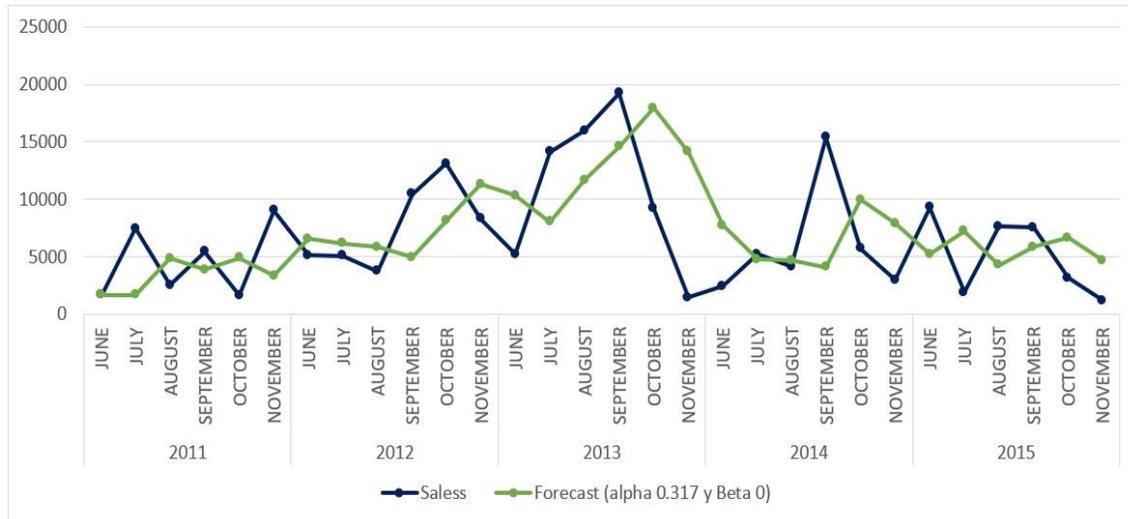

Figure 12. Holt's method plot

Figure 13 shows the spreadsheet with the data for Winter's method. As opposed to the exponential smoothing technique, this method also takes into account trend data. Columns M, Q, U, and Y show real sales figures for each month, and calculations for the smoothing component appear in columns N, R, V, and Z. With this technique, forecasts are obtained by multiplying the period (cell N15) by the trend estimate, and adding the result to the smoothing estimate.

Figure 13. Holt's method spreadsheet

Winter's method

This method is used especially when the data series contains seasonality as a component of the trend. Goodwin (2010) indicates that Winter's is the most popular technique because it is simple, has low data requirements, and can be adapted to changes in trends and seasonal sales patterns when they take place.Three-parameter Winter's method

has the best potential to describe data and decrease forecasting error. An additional equation is used to estimate seasonality (Hanke andReitsch, 2006). The four equations used for Winter's (multiplicative) smoothing are:
Series level estimated by exponential smoothing:

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{10}$$

Trend estimate:

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{11}$$

Seasonality estimate:

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s} \tag{12}$$

Forecast for period p in the future:

$$\hat{Y}_{t+p} = (L_t + pT_t)S_{t-s+p} \tag{13}$$

This technique used a seasonal pattern length of six periods, and calculations were carried out using α (smoothing constant), β (trend), and γ (seasonality). Results found using the best model are presented in Table IV. Figure 14 shows the time series and the forecast using Winter's method.

Table 4. Exponential smoothing techniques

METHOD	α	β	γ	MSE	MAD	R^2
SES	0.317	-	-	23674455.2	3959.43	4.42
Holt's method	0.317	0	-	23674455.2	3959.43	6.75
Winter's method	0.479	0	0.03	29490132.0	4673.64	53.85
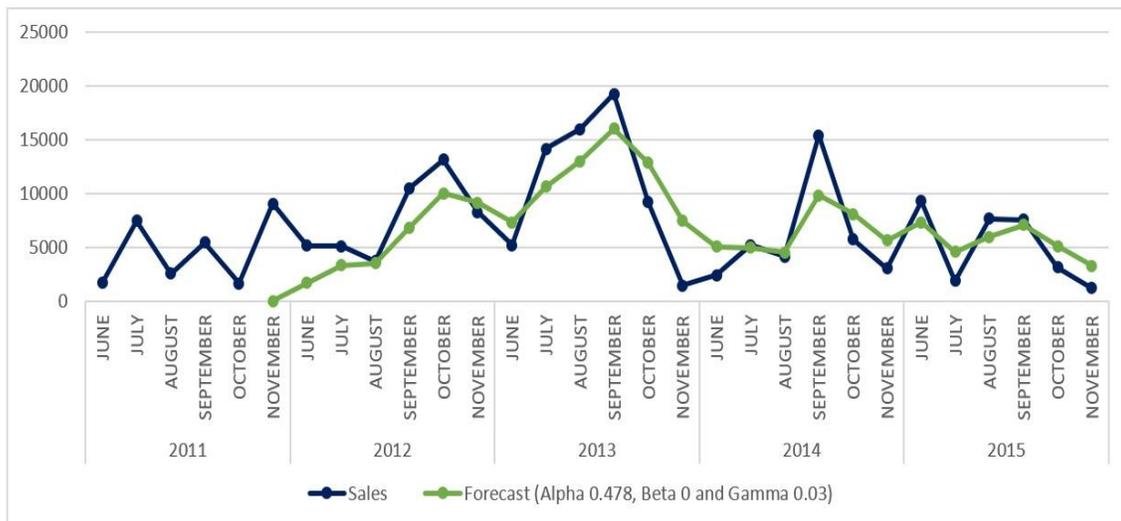
Figure 14. Winter's method plot

Figure 15 presents a spreadsheet with the data for Winter's method calculation. This technique uses three parameters: smoothing constant (cell S23), trend (cell S24), and seasonality (cell S25). Monthly forecasts are obtained by calculating an estimate for each component using equations 10, 11, and 12. The estimated smoothing value is added to the product of period (cell S22) multiplied by trend estimate, and multiplying the result by the seasonality estimate.

Figure 15. Winter's method spreadsheet

V.   RESULTS

Comparison of techniques

To predict the demand of garments, the method with the best performance should be singled out. Hanke and Wichern (2012) provide a mathematical description of ways to evaluate forecasting techniques. Magnitudes of forecasting errors are averaged by MAD.

$$MAD = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| \qquad (14)$$

With ECM, each error or residue is squared, and all results are summed and divided by observations:

$$ECM = \frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2 \qquad (15)$$

Gutiérrez and De la Vara (2012) suggest an initial criteria to evaluate fitting quality that consists in observing how the model fits data in general. Determination coefficient R^2 measures the proportion of variability explained by the data in the model:

$$R^2 = \frac{Variability\ \ explained\ \ by\ the\ model}{Total\ \ variability} = \frac{SC_R}{S_{yy}} \qquad (16)$$

Table V shows the parameters used in each technique, as well as the periods and fitting quality criteria.

Table 5. Forecasting method comparison

METHOD	α	β	γ	Periods	MSE	MAD	R^2
SMA	-	-	-	6	26306190.3	4158.94	2.36
WMA	-	-	-	6	27074151.8	4225.39	2.28
SES	0.317	-	-	1	23674455.2	3959.43	4.42
Holt's method	0.317	0	-	1	23674455.2	3959.43	6.75
Winter's method	0.479	0	0.03	6	29490132.0	4673.64	53.85

The optimal smoothing constant parameter turned out to be the same in both the SES method and in Holt's method, and the same α value was obtained in both cases; Holt's method resulted in a value of β equal to zero. As can be observed in the time series, the technique is congruent with the low sales trend.

As can be appreciated in Table V, which compares the methods, the best methods are SES and Holt's when MSE is used as a criterion, whereas the best method is SES when MAD is used as a criterion. When considering information from the R^2 coefficient, the best method is Winter's; however, this coefficient is unable to explain variations in the model with any of the studied methods. Research by Martínez (2005) and Baeza and Vázquez (2014) demonstrates that using the R^2 coefficient only may lead to considerable error, and their results show that the best model, as indicated by this criteria, does not necessarily result in lower MSE values. Consequently, the best model was selected as indicated by MSE and MAD prediction criteria, and simple exponential smoothing was found to be the model with the best performance for demand forecasting purposes.
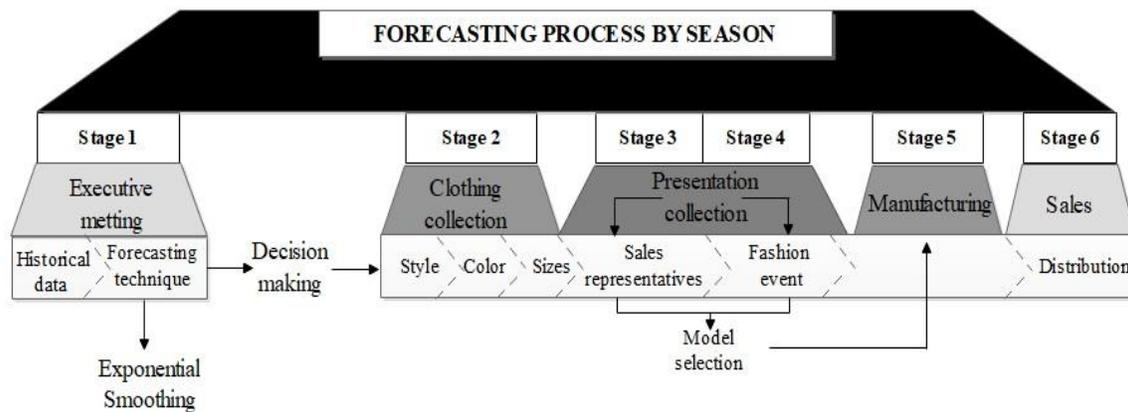

Figure 16. New forecasting process by season

Figure 16 presents the process diagram by season, including the best forecasting technique found by the present study. In stage 1, the executive board will analyze historical data, and the exponential smoothing technique will provide forecasts to assist decision-making based on statistics, rather than on experience, as the firm used to work. Afterward, in stage 2, the clothing collection for the next season will be selected, and so on until products are distributed in stage 6.

Validation
An Excel spreadsheet was used for validation purposes as a tool to help decision makers in the studied firm. The real sales figure for November 2015 was used to obtain the forecast for June 2016. Forecast results for the months of June to November 2016, are shown in Table IV, and the behavior of the forecasts is presented in Figure 17.

Table 6. Demand forecast validation

|	Month	Actual sales	Forecast
2015	**November**	**1206**	**5522.34**
	June	**1394**	**4152.58**
	July	**3782**	**3277.16**
2016	**August**	**4153**	**3437.37**
	September	**2304**	**3664.47**
	October	**2500**	**3232.73**
	November	**2475**	**3000.20**
		MSE	**1840057.67**
		MAD	**1099.58**
		R^2	**44.996**
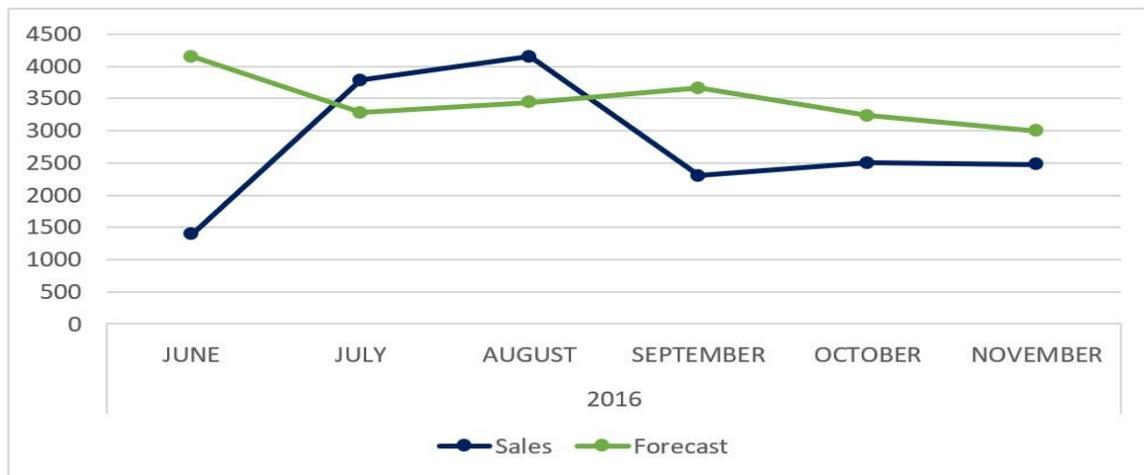
Figure 17. Validation plot

VI.   CONCLUSION

The present study analyzed the sales time series of a textile SME manufacturing knitted garments in order to predict the demand of their products. The time series showed randomness and seasonal patterns, and it also revealed slightly decreasing trend values. Moving average, weighted moving average, exponential smoothing, Holt's method, and Winter's method were used as forecasting techniques. These different techniques were compared, and simple exponential smoothing and Holt's method were found to be the most accurate forecasting methods; specifically, Holt's method produced a value of $\beta = 0$, which confirmed that trend has no significant effect on the model. Each technique was evaluated using MSE, MAD, and R^2 fitting criteria to verify the performance of the different models. Based on our literature review, the best model was selected using prediction criteria MSE and MAD. The best forecasting performance was obtained using the simple exponential smoothing method, which was validated using sales data from 2016.

A forecasting technique allows firms to anticipate the demand they will face so that they can respond promptly to their clients by ordering raw materials in advance and making sure they have enough workforce; forecasting is also useful to plan operations and manage economic resources, among other activities. There are a number of statistical software packages to generate forecasts. However, the present study conducted an adequate analysis of the estimated demand for the studied SME's products and an Excel spreadsheet was developed based on the best of the methods compared by the study. The spreadsheet is an easy to access tool that can be used by decision makers. In the future, forecasting activities carried out by the company every season will be supported by statistical decision-making tools. The present study sought to highlight the importance of providing textile SMEs with tools to underpin their competitive advantage. Although the values of prediction criteria were considerably high, the reliability of the models will be increased in future research by studying different types of artificial neural networks using back propagation and radial base function to predict demand.

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