A Comparison of Machine Learning and Classical Demand Forecasting Methods: A Case Study of Ecuadorian Textile Industry

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Abstract. This document presents a comparison of demand forecasting methods, with the aim of improving demand forecasting and with it, the production planning system of Ecuadorian textile industry. These industries present problems in providing a reliable estimate of future demand due to recent changes in the Ecuadorian context. The impact on demand for textile products has been observed in variables such as sales prices and manufacturing costs, manufacturing gross domestic product and the unemployment rate. Being indicators that determine to a great extent, the quality and accuracy of the forecast, generating also, uncertainty scenarios. For this reason, the aim of this work is focused on the demand forecasting for textile products by comparing a set of classic methods such as ARIMA, STL Decomposition, Holt-Winters and machine learning, Artificial Neural Networks, Bayesian Networks, Random Forest, Support Vector Machine, taking into consideration all the above mentioned, as an essential input for the production planning and sales of the textile industries. And as a support, when developing strategies for demand management and medium-term decision making of this sector under study. Finally, the effectiveness of the methods is demonstrated by comparing them with different indicators that evaluate the forecast error, with the Multi-layer Neural Networks having the best results with the least error and the best performance.

Keywords: Demand Forecasting Methods, Textile industry, Machine Learning, Classical methods, Forecast error.

1 Introduction

All types of organizations require forecasts, since they are the starting point for many plans that, in the short, medium, and long term, are made with the aim of increasing competitiveness in global markets, which are totally changing and aggressive in terms of the strategies they adopt to achieve their survival. The aim of forecasts is to serve as a guide, for an organization, when estimating the behavior of future events; in production, they would trace the course of action of a production planner. It allows to determine the quantities of products to be satisfied in the coming months, the number of workers that would respond to fluctuations in demand or even to plan the size, location, etc., of new facilities. The aim is for the forecasts themselves to minimize the degree of uncertainty to which the input information to different processes is subject, so that decision-makers can generate effective results for the industry.

Today, manufacturing or service companies face the challenge of implementing new organizational and production techniques that allow them to compete in the marketplace. For this reason, several investigations have been developed on demand forecasting, to develop low-cost computational methods for dealing with forecast uncertainties [1]. In Ecuador, the textile industry is one of the sectors with the highest participation in manufacturing, representing 29% of the total of these companies. For these textile and clothing industries, effective planning will facilitate their survival in an increasingly demanding market [2].

Recent changes in the Ecuadorian context have shown the existence of variability in the tariff rates imposed on imports, both of finished products and raw materials. This has caused consumers to reduce purchase levels for certain products, because of price increases, causing uncertainty in the demand for these products. Influencing decisively during the forecast that the textile industry currently makes, variables such as sales prices of textile products, inflation, consumer price index, unemployment, market competition.

Currently, textile industry does not have the effective application of demand forecasting methods that provide solutions for decision making. That they consider all the frequent changes that occur in these companies, for the subsequent marketing and sales of the goods produced. That is why this work focuses on demand forecasting for textile products through a comparative analysis of a set of classical and machine learning methods, which provide an adequate development of demand forecasts.

The remaining of this manuscript is structured as follows: Section 2 sets out a review of the main related works to the subject of this paper. Section 3 describes the case study and Section 4 the demand forecasting methods applied. The results and comparison of forecasting errors are presented in Section 5. Finally, the conclusions are shown in Section 6.

2 Related Works

Forecasting is very useful, as it is used as input to a great number of key processes in companies. In 2015 Seifert et al [3] study the variables that influence the effectiveness of demand forecasting in the fashion industry, presenting the implications for building decision support models. In this way the development of accurate forecasts also aids in decision making [4]. Prak and Teunter propose a general method for dealing with forecast uncertainty in inventory models, the estimation of which is applicable to any inventory and demand distribution model [5].

In 2017 Gaba et al [6] considering some heuristics to combine forecast intervals and compare their performance, obtaining satisfactory results. Other researches [7] studies the problem of multiple product purchases, demand forecast updates and orders. Classification criteria for forecasting methods are also provided [8].

To make a forecast, it is necessary to have quantitative information on demand behavior over time, with analysis using classic statistical techniques such as ARIMA, Holt-Winters, among others, the most widely used to predict their behavior [4, 9].

For many years, this type of analysis has been carried out using linear methods that can be conveniently applied. However, the existence of uncertainty and non-linear relationships in the data largely limits their use. Therefore, it is necessary to use techniques capable of reflecting such behavior and this is where, lately, the use of artificial intelligence techniques is being applied in forecasting demand with much greater force. By the year 2018, in [10] propose a method that uses forecasting and data mining tools, applying them with a higher level of precision at the client level than other traditional methods. Subsequently, [11] examines the exponential smoothing model in the context of supply chain use and logistics forecasting, performing microeconomic time series forecasting.

The development of these innovative methods has led to satisfactory solutions in several areas, with the application of Artificial Neural Networks (ANN), Bayesian Networks (BNs), Naïve Bayes, Support Vector Machine (SVM), Random Forest, among other data mining and machine learning techniques that surpass in accuracy and performance the classic methods [12–14]. In recent years, these machine learning techniques have become very popular in time series forecasting in a large number of areas such as finance, power generation and water resources, among other application [15, 16]. Several authors have used different techniques to demand forecast [17], of the agricultural supply chain [18]. Forecasting urban water demand [19], and forecasting through BNs have also played a key role [20]. Gallego et al [21] made a robust implementation using a Bayesian time series model to explain the relationship between advertising costs of a food franchise network. Also, hybridization methods and comparison of predictions based on ANN and classical statistical methods [22, 23].

From the literature review it appears that the applications of the different methods, mainly of machine learning and artificial intelligence, are the most used at present and that they have given the best results in the demand forecasts development, even more under uncertainty. However, the application of these forecasting methods in the textile industries is not very wide, even more so in small companies that handle information in an empirical way, where the planners experience is the main source for demand forecasting and production planning.

On this basis, this paper applies different methods of forecasting demand based on the need to make a forecast that contemplates the reality of the present scenarios, using historical series and comparing them to determine the most suitable for the textile sector. Each method is adapted according to the data and input variables, training process, to achieve the best results and reach the highest accuracy and quality in the demand forecast. The comparison between the quality of the applied methods is made based on the indicators mean absolute percentage error (MAPE) and root mean square error (RMSE), observing that the best method is ANN. Details about the case study and the demand forecasting methods are provided in the following sections.

3 Case Study Description

The textile industries studied use the initial inventory and sales forecast of a given product, a planner can calculate the amount of production needed per period to meet the expected demand of customers. This calculation becomes more complex when dealing with several products, where forecasting errors and capacity constraints can lead to uncertainty in the planning process. From this, problems are detected in these companies, where there is an inadequate or non-existent demand forecast, insufficient market analysis, and increased operating costs. As well as an inadequate production planning, with high levels of inventory with little rotation, all this influenced greatly by the appearance of an intermittent demand and uncertainty in the same one, affecting directly the levels of service and the strategy of orders and a suitable demand forecast that facilitates the decision making in the production planning of this sector in study.

The development of this research will be done by means of an analysis of methods used in the forecast of the demand. For this purpose, historical data will be taken from a textile industry, which already has a planning system. This will seek greater stability in production planning, generate alternatives and make companies in this important sector more profitable. An integrated approach will be proposed for demand forecasting in the medium term using this historical data, by comparing the performance of classical and machine learning methods. Where the factors to be considered are indicated, such as the identification and pre-processing of the information with which the time horizon of the forecast is analyzed.

The company under study in this paper is a medium manufacturer and distributor industry of textile products, which operates in northern Ecuador. Using a set of forecasting methods and data from historical series of Sublimated Uniforms, Sport T-shirts, Sublimated T-shirts and Polo T-shirts, defined consecutively as Stock Keeping Unit (SKU), with the objective of obtaining more solid predictions with less forecasting error and improve compliance in deliveries to the customer thus increasing their satisfaction. To this end, data is available for these textile products in demand between 2016 and 2019. Every day, sales orders, and orders for these 4 main products are recorded. Fig. 1 clearly shows the behavior of the demand forecast in relation to previous years.

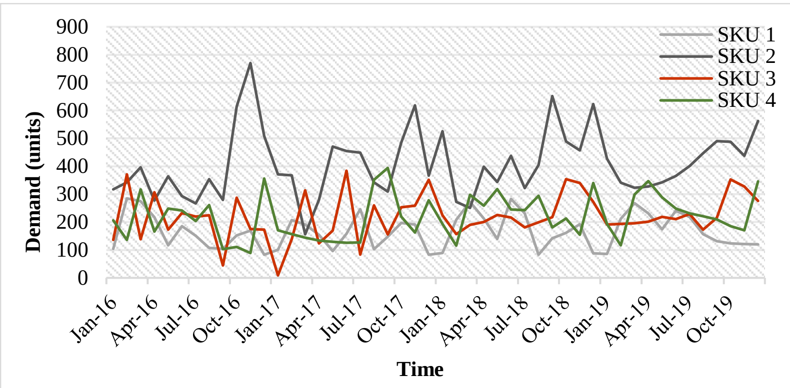

Fig. 1. Dataset textile industry.

The demand study seeks to analyze and predict its behavior in the future based on the analysis of a set of classic and machine learning methods, in addition to the diagnosis of the forecasting process that the industry initially carries out. Finally, a demand forecasting framework is designed for the company under study based on methods used through R programming language.

4 Demand Forecasting Methods

Different methods are used to develop demand forecasting, which can be adapted to specific data, considering all the variables involved in the process and the conditions of each production environment. In our case, the methods used only take time as an independent variable, with a period of analysis per year, according to the historical data provided by the case study industry.

In this study, several classical time series and causal relationship methods are applied to demand forecast, including Hold-Winters, STL Decomposition and ARIMA, which are some of the most used methods in this area under study. Methods based on artificial intelligence include BNs, ANN, SVM and Random Forest. The application of the above methods to the case study, as well as their quality, is briefly described below.

Classical methods

These time-series based methods are relatively easy to apply and can generate accurate predictions for demand. They have become one of the most important tools during forecasting due to their wide range of applicability and flexibility of use. The ARIMA model [9] is a classical forecasting model that combines autoregressive (AR) and moving average (MA) components with additional differing time series (I).

One of the most widely used methods is the Hold-Winters, effectively adapting to changes and seasonal patterns. It allows accurate forecasting of periodic series with few training samples [24]. Represented by smoothing equations and for the forecast by Eq. (1).

$$\widehat{X_t}(k) = (S_t + kT_t)I_{t-s+k} \tag{1}$$

S_t, T_t y I_t represent the smoothing, level, trend, and seasonality equations. Where the observed values are projected to obtain the forecasts $\widehat{X_t}(k)$.

Also, the STL Decomposition method, a robust and accurate method that analyzes time series. It decomposes time series into trends, seasonality, cycles, and random variations.

Figure 2 shows the historical data of the last 4 years distributed in 12 months, on which the multiplicative decomposition is performed analyzing its trend, seasonality and randomness.

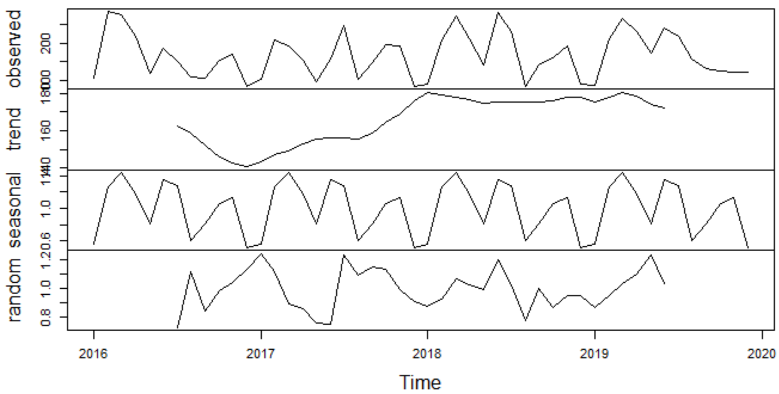

Fig. 2. Descomposition of multiplicative time series.

Naive Method is an estimation technique that only uses the previous year's actual data as a forecast for the next period, without adjusting it or trying to establish causal factors. The application of this method is shown in Fig. 3.

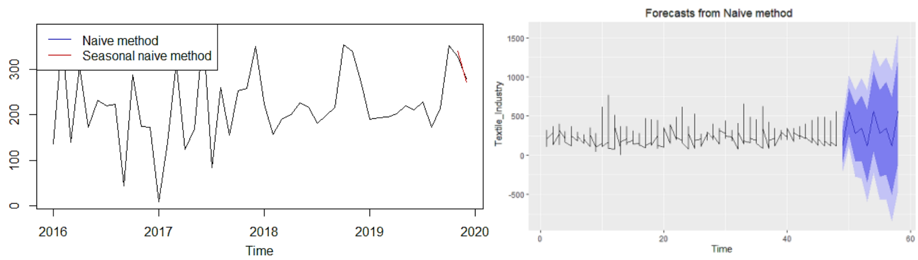

Fig. 3. Naive Method Application.

Machine Learning Methods

According to the related works, an exploration of machine learning techniques is conducted to demand forecasting. Based on [12], a typical specification of demand for product *j* of group *h* on the market *m* at time *t* would be:

$$Y_{jhmt} = f(\mathrm{X, D, p})'\beta + \zeta_{hm} + \eta_{mt} + \epsilon_{jmt} \tag{2}$$

Where *f* generates interactions between observations (X), products (*D*) and prices (*p*). The dummy variables are represented by ζ_{hm}. Seasonality by the term η_{mt}, which varies according to a period of time.

Support vector machines (SVM) establish tolerance margins to minimize the error, looking for the optimal hyper plane as a decision function, maximizing the prediction margin [13], which using a linear kernel method would be represented as in Eq. (3).

$$y = b_0 \sum_{i=0}^{m}(\alpha_i - \alpha_i^*) \cdot (x_i\ , x\ ) + b \tag{3}$$

During the training process, the radial base kernel coefficient and the regularization constant are set and updated using data during each iteration. The accuracy of the method, when implemented with the case study data is adjusted to 97% with a computational cost of less than one minute, as shown in Fig. 4.

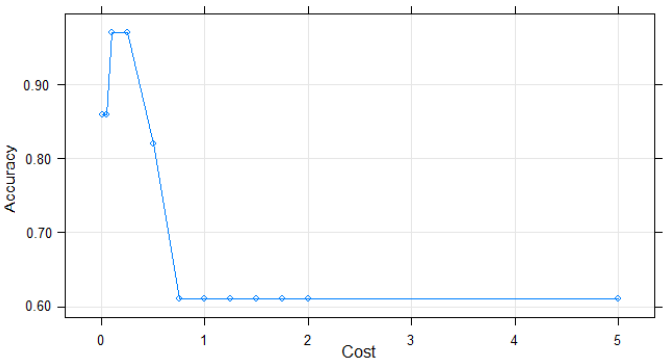

Fig. 4. SVM Accuracy.

In Bayesian analysis, forecasts are based on the predictive distribution after the event [20]. It is insignificant to simulate from this, where the probability of subsequent inclusion is indicated for each predictor, as discussed in Eq. (4).

$$p(\tilde{y}|\mathbf{y}) = \int p(\tilde{y}|\phi)p(\phi|\mathbf{y})\,d\phi \tag{4}$$

Where $\tilde{y}$ is the set of values to predict, $p(\tilde{y}|\phi)$ the set of random extractions $p(\phi|\mathbf{y})$. The application of the method is presented below in Fig. 5, as a function of the distribution and demand forecasting.

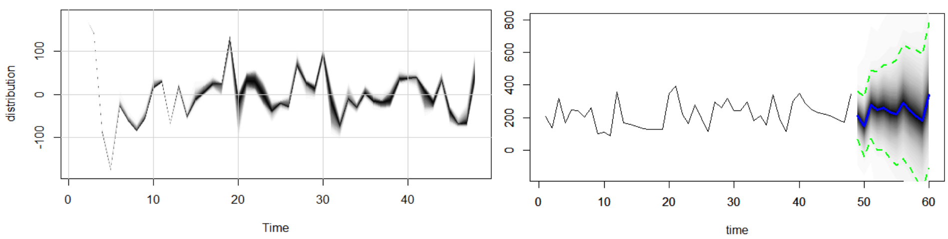

Fig. 5. Distribution and forecasting demand with BNs application.

The Random Forest algorithm has been extremely successful as a general-purpose classification and regression method [25]. It is proposed that by combining several random decision trees and aggregating their predictions by averaging, it has demonstrated excellent performance in scenarios where the number of variables is greater than the observations. The behavior of the relative error of the method when applying the combination of random trees for the prediction is presented in Fig. 6.

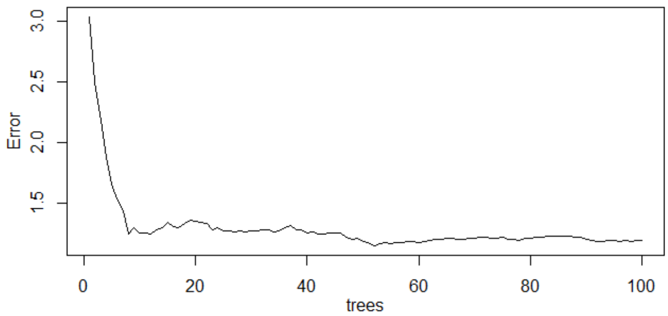

Fig. 6. Error with Random Forest Application.

The applications of neural networks in demand forecasting have been significant, from the typical single-layer hidden power neural network, to multilayer, a MLP (multi-layer perceptron) network specially designed for time series forecasting [23]. The function represented by a single-layer MLP with a single output is shown in Eq. (5).

$$f(Y, w) = \beta_0 + \sum_{h=1}^{H} \beta_h\, g\left(\gamma_{0i} + \sum_{i=1}^{I} \gamma_h\, Y_i\right) \tag{5}$$

Where w is the weight of each neuron, β the output layers and γ the hidden. The variables β_0, γ_{0i} represent the biases of each neuron.

The configuration of the MLP neural network and the application result is shown in Fig. 7.

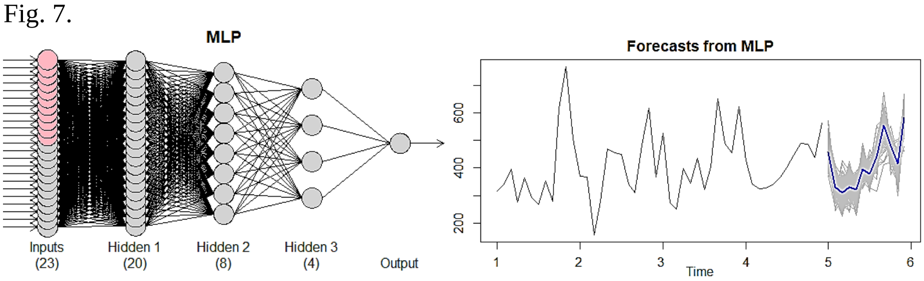

Fig. 7. MLP for demand forecasting.

5 Results and Discussion

The industry in the textile sector under study is located in the north of Ecuador. It is a small company with 25 workers. In order to apply the methods of demand forecasting, the historical demand from 2016 to 2019 of Sublimated Uniforms, Sport T-shirts, Sublimated T-shirts and Polo T-shirts, the main products of this Ecuadorian textile industry, are available. These products represent the largest quantity of orders and sales of the company, with a unit of SKU measurement and a period of 48 months. Based on the previous historical data, the methods described above are applied, obtaining the demand forecast for the next 12 months. Below, Fig. 8 shows the forecasts graphs obtained by applying each method.

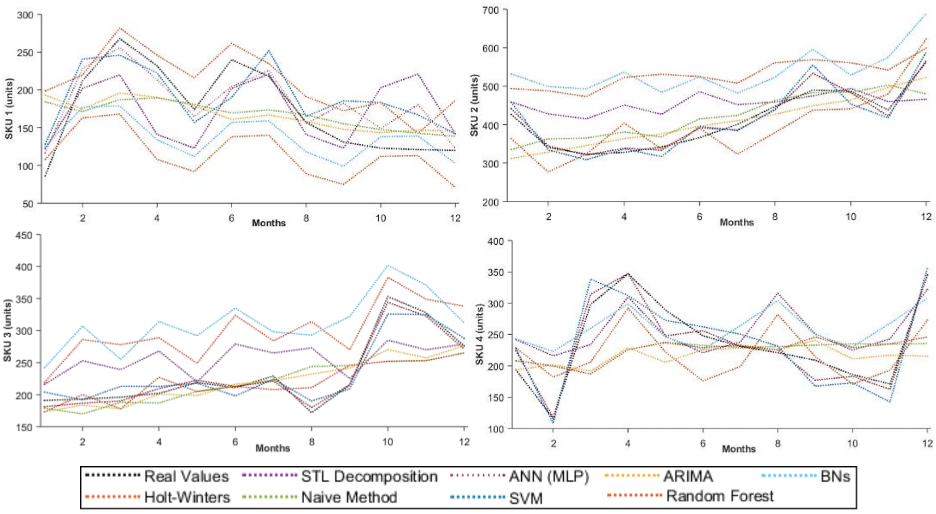

Fig. 8. Comparison of results between methods by SKU.

To evaluate the performance of the applied methods, error measurements comparing the difference between the forecast and the real value are used, such as mean absolute percentage error (MAPE) and root mean square error (RMSE), indicators of forecast accuracy widely used in time series analysis. Which can respectively expressed by Eqs. (6) and (7).

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{y_t - \widehat{y_t}}{y_t} \right| \cdot 100\% \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} \left(y_t - \widehat{y_t}\right)^2} \tag{7}$$

In these equations the variables include the number of samples n, y_t is the real demand for textile products and $\widehat{y_t}$ is the estimate of this. The ideal value for statistical metrics is zero, the closer they are, the greater the forecast accuracy, indicating a better performance of the method used. Fig. 9 shows the MAPE and RMSE results for each method analyzed.

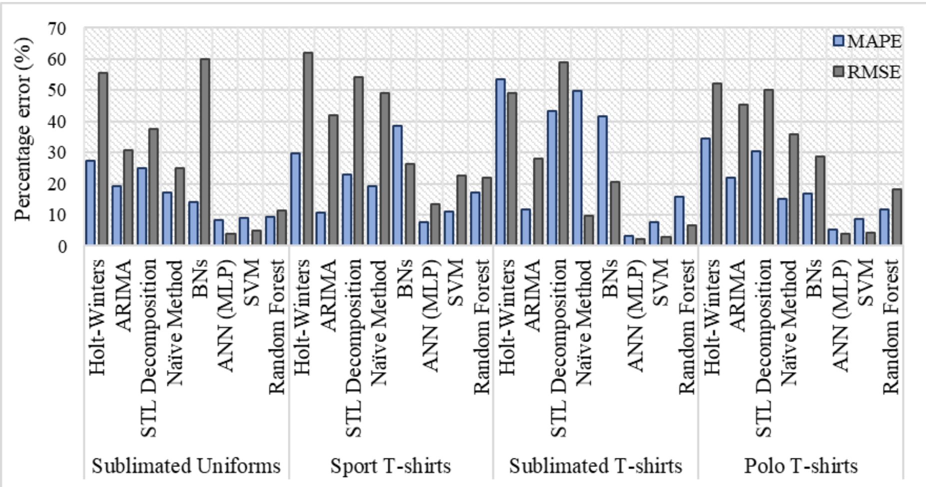

Fig. 9. Errors comparison of the applied forecasting methods.

From the comparative analysis represented in the figure above, it can be determined that each product behaves differently, where the best results are obtained with ANN (MLP). With greater accuracy than the other methods and the least error in the forecast, the best performance is also obtained for each product analyzed. This value is significantly different from those of the other methods and even more so from the classical forecasting methods, where it demonstrates the quality and accuracy of the latter in forecasting demand and in comparison, with evaluation metrics. Fig. 10 shows the behavior of MAPE for each model, where the SVM obtains less variability, that is, less dispersion of error on average, but by analyzing each SKU in particular, the ANN (MLP) develop better quality and precision in the results with respect to the other methods applied.

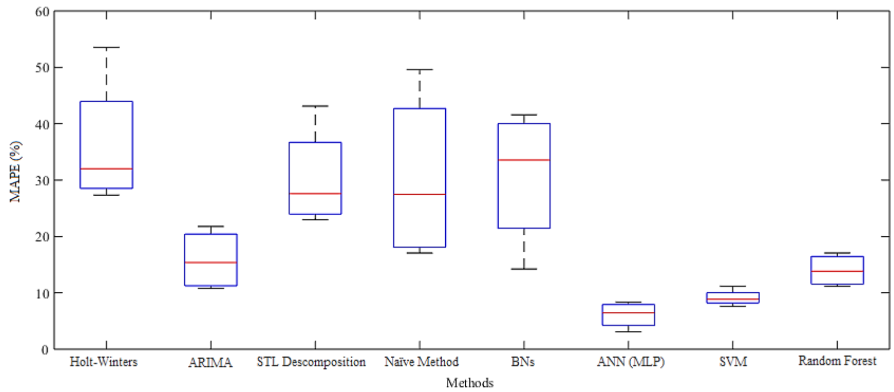

Fig. 10. MAPE analysis by each method.

By analyzing and comparing the demand forecast and the evaluation metrics used in the case study industry, it is identified that the most suitable method is ANN (MLP). Achieving an optimal network configuration through enhancement processes, to determine the nodes of each hidden layer: 22, 8, 4. Obtaining the best results of the forecast in the second iteration in the ANN (MLP) retraining, reaching the best values of the MAPE and RMSE indicators with a low computational cost. That, with respect to the other methods applied, they obtain indisputably the best results in terms of the performance indicators analyzed.

6 Conclusions

Accurate demand forecasting is essential to increase companies' competitiveness as multiple processes use it as input to make decisions. Ecuador's textile industry is no exception. This industry is characterized by high inventory levels with low turnover, increased operating costs, where the demand forecast is inadequate or non-existent, with uncertainty in the same, which is why it requires forecasting methods that consider all possible scenarios and provide feasible solutions for decision making.

In the present article we have applied more classic methods of demand forecasting like Holt-Winters, ARIMA, STL Decomposition, Naïve Method, and others of more actuality like Random Forest, ANN (MLP), SVM, BNs. The objective is to be able to compare the accuracy of these methods and determine the one that best suits the textile sector in Ecuador, with the ANN (MLP) having the best results in each product analyzed.

As a result of the analyses carried out in the study, it can be concluded that the use of machine learning methods for the forecasts development, when there is a large amount of data and uncertainty in them, achieve better results, which greatly influence the forecasts accuracy. A better quality forecasting will serve as a basis, for the use of resources and labor, for a better production planning of the Ecuadorian textile industry and in this way to improve the manufacture times, as well as, the delivery on time to the clients, increasing their satisfaction and with it, the sales.

As a future work, it is proposed to go deeper into the configuration of machine learning methods, analyzing in detail the accuracy and computational cost of the solutions during the demand forecasting development.

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References

1. Silva, P.C.L., Sadaei, H.J., Ballini, R., Guimaraes, F.G.: Probabilistic Forecasting With Fuzzy Time Series. IEEE Trans. Fuzzy Syst. (2019). https://doi.org/10.1109/TFUZZ.2019.2922152.
2. Lorente-Leyva, L.L., et al.: Optimization of the Master Production Scheduling in a Textile Industry Using Genetic Algorithm. LNCS. 11734 LNAI, 674–685 (2019). https://doi.org/10.1007/978-3-030-29859-3_57.
3. Seifert, M., Siemsen, E., Hadida, A.L., Eisingerich, A.B.: Effective judgmental forecasting in the context of fashion products. J. Oper. Manag. 36, 33–45 (2015). https://doi.org/10.1016/j.jom.2015.02.001.
4. Tratar, L.F., Strmčnik, E.: Forecasting methods in engineering. IOP Conf. Ser. Mater. Sci. Eng. 657, 012027 (2019). https://doi.org/10.1088/1757-899X/657/1/012027.
5. Prak, D., Teunter, R.: A general method for addressing forecasting uncertainty in inventory models. Int. J. Forecast. 35, 224–238 (2019). https://doi.org/10.1016/j.ijforecast.2017.11.004.
6. Gaba, A., Tsetlin, I., Winkler, R.L.: Combining interval forecasts. Decis. Anal. 14, 1–20 (2017). https://doi.org/10.1287/deca.2016.0340.
7. Zhang, B., Duan, D., Ma, Y.: Multi-product expedited ordering with demand forecast updates. Int. J. Prod. Econ. 206, 196–208 (2018). https://doi.org/10.1016/j.ijpe.2018.09.034.
8. Januschowski, T., et al.: Criteria for classifying forecasting methods. Int. J. Forecast. 36, 167–177 (2020). https://doi.org/10.1016/j.ijforecast.2019.05.008.
9. Box, G. E., Jenkins, G. M., Reinsel, C., Ljung, M.: Time Series Analysis: Forecasting and Control, 5th Edition. John Wiley & Sons, Inc. (2015).
10. Murray, P.W., Agard, B., Barajas, M.A.: Forecast of individual customer's demand from a large and noisy dataset. Comput. Ind. Eng. 118, 33–43 (2018). https://doi.org/10.1016/j.cie.2018.02.007.
11. Bruzda, J.: Quantile smoothing in supply chain and logistics forecasting. Int. J. Prod. Econ. 208, 122–139 (2019). https://doi.org/10.1016/j.ijpe.2018.11.015.
12. Bajari, P., Nekipelov, D., Ryan, S.P., Yang, M.: Machine learning methods for demand estimation. Am. Econ. Rev. 105, 481–485 (2015). https://doi.org/10.1257/aer.p20151021.
13. Villegas, M.A., Pedregal, D.J., Trapero, J.R.: A support vector machine for model selection in demand forecasting applications. Comput. Ind. Eng. 121, 1–7 (2018). https://doi.org/10.1016/j.cie.2018.04.042.
14. Herrera-Granda, I.D., et al.: Artificial Neural Networks for Bottled Water Demand Forecasting: A Small Business Case Study. LNCS. 11507 LNCS, 362–373 (2019). https://doi.org/10.1007/978-3-030-20518-8_31.
15. Dudek, G.: Multilayer perceptron for short-term load forecasting: from global to local approach. Neural Comput. Appl. (2019). https://doi.org/10.1007/s00521-019-04130-y.

16. Salinas, D., Flunkert, V., Gasthaus, J., Januschowski, T.: DeepAR: Probabilistic forecasting with autoregressive recurrent networks. Int. J. Forecast. (2019). https://doi.org/10.1016/j.ijforecast.2019.07.001.
17. Weng, Y., Wang, X., Hua, J., Wang, H., Kang, M., Wang, F.Y.: Forecasting Horticultural Products Price Using ARIMA Model and Neural Network Based on a Large-Scale Data Set Collected by Web Crawler. IEEE Trans. Comput. Soc. Syst. 6, 547–553 (2019). https://doi.org/10.1109/TCSS.2019.2914499.
18. Zhang, X., Zheng, Y., Wang, S.: A Demand Forecasting Method Based on Stochastic Frontier Analysis and Model Average: An Application in Air Travel Demand Forecasting. J. Syst. Sci. Complex. 32, 615–633 (2019). https://doi.org/10.1007/s11424-018-7093-0.
19. Lorente-Leyva, L.L., et al.: Artificial Neural Networks for Urban Water Demand Forecasting: A Case Study. J. Phys. Conf. Ser. 1284 (1), 012004 (2019). https://doi.org/10.1088/1742-6596/1284/1/012004.
20. Scott, S.L., Varian, H.R.: Predicting the present with Bayesian structural time series. Int. J. Math. Model. Numer. Optim. 5, 4–23 (2014) https://doi.org/10.1504/IJMMNO.2014.059942.
21. Gallego, V., Suárez-García, P., Angulo, P., Gómez-Ullate, D.: Assessing the effect of advertising expenditures upon sales: A Bayesian structural time series model. Appl. Stoch. Model. Bus. Ind. 35, 479–491 (2019). https://doi.org/10.1002/asmb.2460.
22. Han, S., Ko, Y., Kim, J., Hong, T.: Housing Market Trend Forecasts through Statistical Comparisons based on Big Data Analytic Methods. J. Manag. Eng. 34, (2018). https://doi.org/10.1061/(ASCE)ME.1943-5479.0000583.
23. Lee, J.: A neural network method for nonlinear time series analysis. J. Time Ser. Econom. 11, 1–18 (2019). https://doi.org/10.1515/jtse-2016-0011.
24. Trull, O., García-Díaz, J.C., Troncoso, A.: Initialization methods for multiple seasonal holt-winters forecasting models. Mathematics. 8, 1–16 (2020). https://doi.org/10.3390/math8020268.
25. Biau, G., Scornet, E.: A random forest guided tour. Test. 25, 197–227 (2016). https://doi.org/10.1007/s11749-016-0481-7.