UNIVERSIDAD SAN FRANCISCO DE QUITO USFQ

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Developing an Inventory Management System Based on Artificial Neural Network Forecasting in an Industrial Supply Distributor: A Case Study.

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RESUMEN

El objetivo del presente estudio es desarrollar pronósticos y políticas de manejo de inventarios basados en técnicas de pronósticos en una empresa distribuidora de repuestos, herramientas, accesorios de maquinaria y materiales de construcción. Para ello, se utilizó el método de clasificación ABC multicriterio para la clasificación de los productos, seguido del modelo de aprendizaje no supervisado K-means para agregar los productos. Posteriormente, múltiples técnicas de pronóstico, incluyendo Redes Neuronales Artificiales fueron empleados, obteniendo un error promedio del 18%. Se utiliza un modelo de optimización para desagregar los clusters y finalmente, se aplica el modelo de inventarios Q,R Servicio Tipo II para obtener la cantidad y el punto de reorden para 1600 SKUs

Palabras Clave: Pronosticos con ANN; Pronósticos de series de tiempos; manejo de inventarios; data analytics; case study

ABSTRACT

The goal of the present study is to develop forecasts and inventory management policies based on various forecasting techniques in a spare parts, tools, machine accessories, and construction materials distributor. For this purpose, a multicriteria ABC classification method is used for product classification; followed by an unsupervised K-means clustering method for product aggregation. Then, multiple forecasting techniques, including Artificial Neural Networks (ANN) are tested, obtaining an 18% average forecasting error. Cluster disaggregation is done through an optimization model, and finally, the Q,R Service Type II model is applied to obtain the quantity and reorder points of 1600 SKUs.

Keywords: ANN forecasting; time series forecasting; inventory management; data analytics; case study

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1. INTRODUCTION

The acquisition of tools and industrial machinery is key in the economic growth of any country, as these industries intervene in the civil construction industry, metalworking industry, energy sector, and many other fundamental industries [1]. In Ecuador, the country where this study was carried out, this sector has an annual growth of 8% [2], reporting an average of 700 million dollars in sales on machinery and hardware items [3].

The present study was conducted in DAV Company, a growing retailer established in 2007, with warehouses/Points-of-sale (POS) in two major cities in the country [54]. DAV Company sales tools and accessories for drilling, threading, milling, insert turning, measuring processes, and construction materials [54].

The company has more than 5000 active stock keeping units (SKUs), and the demand and inventory planning was done empirically, based on the sales department decisions, before this study [54]. However, inventory management problems like stockouts for some products, and others being held in warehouses for large periods of time, have been reported and were becoming more and more common, due to rapid growth of sales, the large variety of products and the existence of two POS with different market behaviours [54]. As a result, an inventory turnover, which is a measure of how efficient the company is managing inventory, of 1.9 was reported the prior year, in comparison to a 4.2 industry average [4] [5]. To address these problems, the development of demand forecasting and inventory management policies for the company is suggested [6] [7], according to Operations Analysis and Supply Chain Management (SCM) literature [6] [7] [8].

Therein, the main goal of this study was to develop a demand forecasting and inventory management system through the analysis of historical sales information and different mathematical models, to minimize inventory costs of DAV Company.

The present paper is structured as follows. Section 2 discusses the relevant literature. Subsequently, Section 3 describes the methodology used to address the defined problem. Section 4 presents the results of applying the methodology to real data of DAV Company. Finally, the last two sections present the conclusions and discussions of the study.

2. LITERATURE REVIEW

2.1 Data Pre-processing

Cleaning and processing historical demand data need to be done before forecasting to minimize errors [6]. Ghiani (2013) [9] proposes the following processes to prepare the demand database:

(1) Remotion of invalid data and insertion of missing data

(2) Detection of outliers

(3) Data classification

(4) Data aggregation

In step (1), null values need to be removed, and insertion of missing data needs to be considered [9]. Regarding step (2), Rennie et al. (2021) state that outliers caused by extraordinary events need to be identified and if needed, removed [10].

DAV Company's main customers belong to the construction sector [54]. Considering how the Covid-19 pandemic affected this industry, which was completely stopped at certain times throughout 2020 [11], outlier detection was critical for the present study. Sales data from 2017 to 2020 was available. How to treat 2020 data in forecasting was still debated as this work was being carried out. Sohrabpour (2020) et al., decided to use the demand data during the pandemic for forecasting sales in a food export company [12], while Puga et al. (2021), in their study on a flower export company [13], and Malefors et al. (2021), in a Swedish catering industry [14], did not use 2020 data. No study on forecasting, addressing this topic, was found by the authors in the spare part retail, industrial accessories retail or hardware retail sectors.

Controlling an inventory management system for each product is costly, so the trade-off between the cost of maintaining the system and the benefit of using it, must be considered by classifying and prioritizing products [6], as stated in step (3). The multicriteria ABC classification method has gained popularity in recent years, because of its versatility to consider different variables, relevant to a specific problem [17]. Rego & Mesquita (2010) conclude that there are two main characteristics needed to classify industrial spare parts for inventory management: 1) a variability measure, and 2) a measure of the phase of the life cycle or growth of the products [18]. Guimaraes et al (2020) emphasize the importance of the first characteristic for spare parts in agricultural and construction machines, to prioritize intermittent and variable demand over known demand in inventory management systems [19]. Sirovia & Rodriguez (2019) agree on using both variability and sales growth criteria and argue that handling and shipment criteria like product size or shape, are included by other authors as important characteristics in spare part management [20], which was also addressed in the classification of products on automobile rubber components on a study conducted by Bajali (2014) [21].

Because aggregate forecasts tend to have a relatively small variance compared to individual forecasts [7] [8] [9], and aggregation reduces the number of observations with value zero [24] [25], step (4) is needed. SKUs should be aggregated based on similar demand patterns [6]. Choudhary et al. (2008), argues that one advantage of using Data Mining is to categorize large volumes of SKUs [26]. Hierarchical agglomerative clustering (HAC), and K-means clustering, were used in the present study and demonstrated to have an efficient and more precise result than non-aggregation or aggregation based on predefined product families by Ruitenbeek (2019) and Wang et al. (2019) [27] [28].

2.2 Forecasting Techniques

Qualitative forecasting techniques primarily consist of human judgement [29], while quantitative methods are based on mathematical modelling and can be classified in causal and non-causal models (time series models) [6] [29]. Causal methods, like regression, use predictor variables like price, discounts, season, among others. [29], to capture trend and seasonality and can generate satisfactory results. An example can be seen in a study conducted by Said et al.'s (2013) for demand forecasting in the retail sector (industry not specified); where Y is the future sales prediction of a determined product, X1 is advertising spending, X2 is promotional expenses, and X3 is quarterly sales of its main competitor [30]. On the other hand, time series models rely solely on past data of the variable that is being forecasted [6]. Different methods are categorized depending on the pattern of the historical data, that is, stationary series, series with tendency and seasonal series [6] [31]. Stationary series are commonly predicted with moving average and exponential smoothing [6]. Holt's model or double exponential smoothing can be used to track time series with linear tendency [6]. Finally, Winters' model or triple exponential smoothing is used in seasonal time series [6].

The Croston model was developed to handle intermittent demand [32], with demonstrated high performance, such as in the study conducted by Sani and Kingsman (1997) in a spare parts depot in the United Kingdom [33] or in another study carried out in the aviation field by Ghobbar and Friend (2002) [34]. In the former study, compared to a 12-month moving average model, Croston model proved to have the second lowest cost and service level regrets (percentage error measure based on using one method compared to the best) [33]. In the latter study, MAPE was used as a measure of error in conjunction with a predictive error-forecasting model, where the Croston model proved to have better performance in comparison to other classical empirical forecasting models used in the aviation industry [34]. Nevertheless, one of the limitations of the Croston model is that unless a new positive demand occurs, none of the parameters are updated [32]. Lastly, novel variants of the Croston model have appeared, such as the Modified Croston, the Forward Modified Croston, the Babai approach, the SBA and the SBJ variations [35] [46].

Additionally, artificial neural networks (ANN) represent another useful technique in causal and historical data-based forecasting. ANN models typically contain three layers, an input layer, a hidden layer, and an output layer [29]. The input layers are the independent variables used as predictors of the model, the training or test set, and the error [31]. The output layer contains the dependent variable, or the variable (set) being forecasted [36]. The basic structure of an ANN for causal forecasting models, according to Shmueli (2020), is presented in Figure 1:

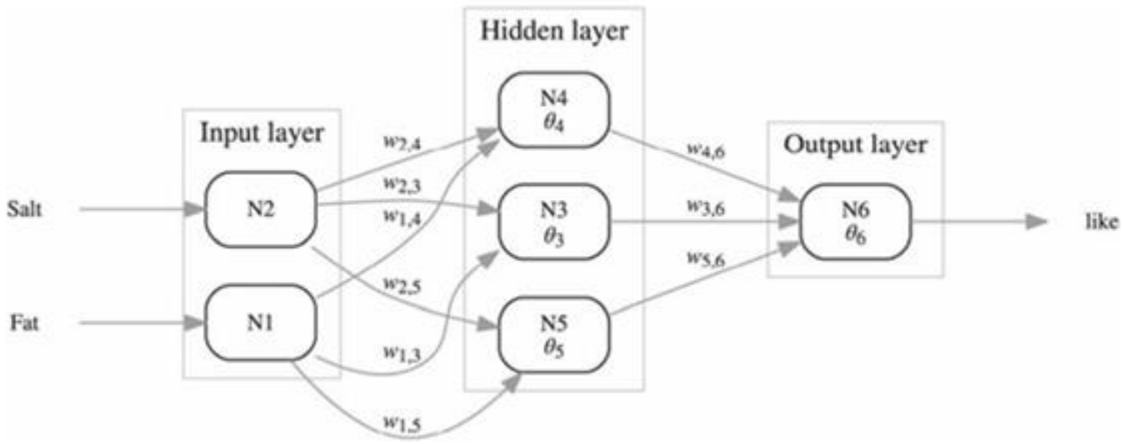

Figure 1. Basic Structure of an Artificial Neural Network. Obtained from Shmueli [4]

In this way, Shmueli (2020) explains how each rectangle represents a neuron and the values of the connected arrows are called weights from node i to node j (wi,j). There are additional bias parameters denoted by θj, which are intercepts for the output from node j [4]. ANN needs to establish an activation function, which determines the output of the ANN by converting the output of a given layer before passing it to the next one, by inserting linearity or non-linearity that enables the network to learn complex patterns in the data [4]. There are several activation functions, however the Sigmoid Tangent, Logarithmic Sigmoid and Rectified Linear Unit activation functions are widely used due to the non- lineal factor they introduce into the neural network, which provides better results in terms of accuracy [68]. Ultimately, the biases and weights need to learn how to minimize loss function through a learning optimization algorithm, which optimally updates the weights [37]. The current optimization algorithm corresponds to the Adam algorithm for stochastic optimization [69]. Many authors recommend Adam due to its computational efficiency, good performance in problems with big datasets and parameters, and with non-stationary data [69][70].

Multiple case studies have been conducted in this area, showing how ANN have a better performance than conventional methods [38][39][40][71]. Chawla and Soni (2019) used Levenberg Marquadt backpropagation, Scaled Conjugate Gradient Backpropagation and Bayesian Regularization learning algorithms to train the ANN model for sales forecasting at Walmart [38]. Multi-layered perceptron ANN with one hidden layer, 22 neurons, TANSIG transfer function and TRAINLM activation function gave the best results according to a series of graphs of demand vs forecasts [38]. A study conducted by Gdowska et al. (2016) used Learning algorithms such as Polak-Ribiére conjugate gradient backpropagation and One Step Secant Backpropagation, were used for demand forecasting in a distribution enterprise [39], with better performance compared to Brown's model, Holt's model, and Winter's model in most cases. One study conducted by the University of Lyon on Dassault Aviation data showed that ANN outperformed other frequently forecasting methods for intermittent demand [40].

Recurrent Neural Network variation proved to have optimal results in demand forecasting in a study conducted by Abbasimehr et al. (2020); specifically, a type of Long Short-Term Memory (LSTM) neural network [58]. The employed data in this study are monthly sale quantities for a product from 2007 to 2017 in a furniture company [58]. In terms of SMAPE (a metric measure that overcomes the asymmetric limitations of MAPE [74]), the multi-layer LSTM proved to have the best performance for time series forecasting [58]. Specifically, LSTM counts with a series of variations; for the present study, the Vanilla LSTM and Bidirectional LSTM were considered. Vanilla LSTM generally gives optimal results with its standard structure consisting of a single hidden unit layer [59]. The Bidirectional LSTM has the additional component of learning the entry sequence backwards and forwards [59]. For multiple periods prediction, LSTM models must follow an Encoder Decoder Model, which is designed for multi-step forecasting [60]. Bidirectional LSTM Encoder Decoder Model (BI-LSTM S2S) has shown tremendous performance in a study conducted in FESCO electric company for day-ahead peak load forecasting [71]. BI-LSTM S2S reached an average MAPE of 4.84%, surpassing other forecasting models performance in normal and special days [71].

Additionally, Convolutional Neural Networks (CNN) have great potential as forecasting methods, as shown by a study conducted by Kang et al. (2020) in forecasting electricity demand, where CNN significantly outperformed RNN and a hybrid model [62]. CNN have the convolutional layer, the pooling layer and the flatten layer, that can determine the most important features of the dataset [61]. Based on [11], [12], [13], [14], [68], [69], [70] and [15] and computational capacity available, the following parameters should be considered:

(1) Optimization Algorithm: Adam

(2) Number of units (LSTM, CNN): 300 Epocs, 500 for LSTM models, 7000 for CNN

(3) Loss function (LSTM, CNN): MSE

(4) Additional hyperparameters for CNN: filters: 64, kernel_size: 2

After demand is forecasted, forecasting performance measures must be considered and calculated. Within these, the Mean Absolute Percentage Error (MAPE) and the Mean Absolute Error, as a percentage of the average demand (MAE%), are the main error measures used in several studies [12] [13] [19] [28] [39]. The first one, MAPE, is commonly used together with the forecasting quality evaluation table proposed by Ghianni (2013), shown in Table 1 [9]. The second one, MAE%, is commonly used as a measure of error for intermittent demand, where MAPE cannot be calculated [6] [9].

Table 1. Evaluation of the quality of a forecasting method's MAPE, proposed by Ghianni [9]

MAPE	Quality of forecasting
<10%	Very Good
>10%, < 20%	Good
> 20%, < 30%	Moderate
> 30%	Poor

2.3 Product Disaggregation

After forecasting each aggregated product, and before inventory modelling, it is important to disaggregate the forecasts, since inventory is managed at SKU level. Nahmias (2013) argues there are very few studies on disaggregation [6], and discusses Hax and Candea (1981) optimization model [52], which was used by Sarmiento (2012) in a forecasting and inventory management project [53]:

$$Minimise \sum \frac{k_j \lambda_j}{Y_j} \tag{1}$$

Subject to:

$$\sum Y_j = X^* \tag{2}$$

$$a_j \leq Y_j \leq b_j \tag{3}$$

Equation (1) sets the objective to minimize the product of the order cost k_j for each j product, and the average historic demand of each j product, λ_j, divided by amount of aggregated units allocated to each j product Y_j. Constraint (2) equals the sum of all units Y_j to the total aggregated units X^*. Constraint (3) presents a minimum and maximum order size for each Y_j product [6] [52].

2.4 Inventory Management Models

A study conducted by Bells University of Technology defined inventory systems as one of the most important business processes [41] [6]. An article published by the Boston Business Journal emphasized the importance of satisfactory inventory control on unusual circumstances [42], such as the Covid-19 Pandemic. This gives companies the task to review their inventory systems to stay profitable and competitive, especially nowadays, with the Covid-19 Pandemic [42].

Nahmias (2015) classified inventory models based on the type of demand and the type of inventory review systems, as explained below. The model classification can be better understood following Figure 2. The first characteristic needed to determine the appropriate inventory model to apply, is if the demand is known, or unknown /stochastic [6]. Once the demand type is determined, the second characteristic is the inventory review system, which can be periodic or continuous. As was the case for this study and most companies nowadays [45] [55], DAV Company has unknown demand and a continuous inventory review system [44]. Thus, a Q, R system was selected for the present study. These variables represent the optimum quantity and reorder point, respectively [6]. When inventory levels reach R, an order of size Q is prepared which will arrive in τ time units [6]. In some studies, variations such as variable lead time [46] and correlation between products sales [48], were modelled. However, this data was not available in DAV Company, so lead time was considered to be deterministic, and product demand independent between products.

When stock-out costs cannot be easily or confidently determined, a service level is used [6] [56]. Service Type 1 works with the probability of not having stockouts during lead time, while Service Type 2, measures the proportion of demand met from stock β [6], which is a more precise form of service level [73]. Q, R Service Type 2 is a model based on the normal distribution, the loss function, and holding cost, order cost and average demand [6]. Its calculation is iterative and converges when the difference between variables Q and R for the last iteration and the previous one is less than 1 unit [6].

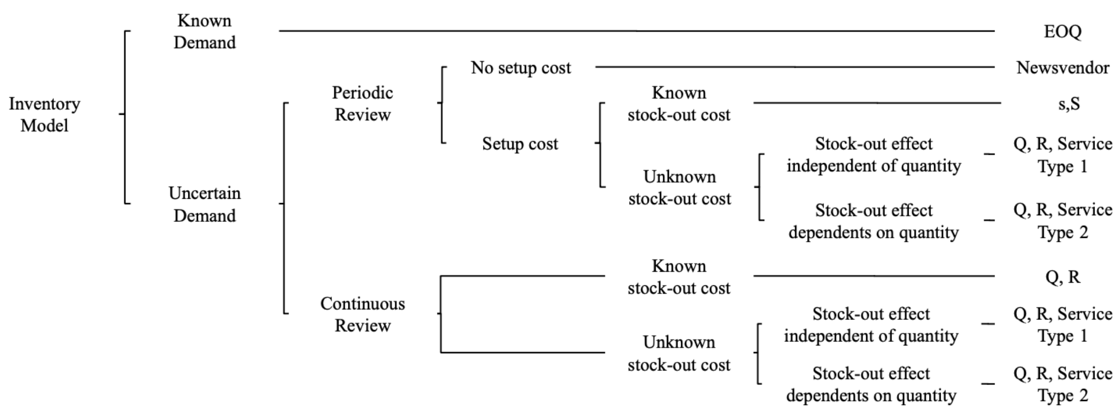

Figure 2. Decision Tree Diagram for Inventory Model Selection. Based on Nahmias [6]

Inventory models are widely used in practice. For instance, Emar (2019) developed and implemented an inventory management system using the EOQ model for laptop spare parts in UPS, one of the largest parcel delivery companies in the world [64]. A study conducted by Reino (2020) in the construction industry, applied the EOQ model and reduced inventory costs by approximately 20% [67]. Regarding the (Q, R) model, Borle et al. (2020) applied it in the pharmaceutical industry and achieved inventory cost savings of 25% [63], while Lasparrilla et al. (2015) accomplished a 99% service level [66]. Chi.Leung (2014), applied the (Q, R) policy with restriction capacity in health care apparel, an achieved a 17-20% cost reduction [65].

3. METHODOLOGY

In order to achieve the planted objectives, a forecasting and inventory methodology was applied. In this study, an adapted form of Montgomery (2013) et al. "The Forecasting Process" methodology was used [8]. This methodology was previously used by Vela (2020) in the oil industry [44], and a modification of it by Jervinen (2017) in the technology industry [47]. The adapted forecasting and inventory process steps are:

(5) Problem Definition: which involves defining:

   (a) The forecasting period: daily, weekly, monthly, etc.

   (b) Forecasting horizon: required number of forecasted periods in the future.

   (c) Goal of the forecasting process: in this case, forecasts will serve as input for inventory management.

(6) Data collection: obtaining historic data or potential assumptions relevant to the forecast.

(7) Data analysis: which includes graphic preliminary review of data, and data pre-processing.

(8) Forecasting Model selection and fitting: application of forecasting models to data and choosing the models that best fit the data.

(9) Inventory Management model selection: application of models to data and choosing the models that best fit the data.

(10) Forecasting and Inventory model deployment: which involves getting the forecasting results and inventory policies to use by the customer.

Step 5 was added to include inventory management. Two steps were not taken into consideration in the scope of this project, both regarding control and validation. In step (3), when using data mining for aggregating time series, and in step (4), when using data mining for forecasting, a 10-step process for data mining, proposed by Shmueli (2020) [31] was used:

(1) Develop an understanding of the purpose of the data mining project.

(2) Obtain the dataset to be used.

(3) Explore, clean, and pre-process the data.

(4) Reduce the data dimension.

(5) Determine the data mining task.

(6) Partition the data.

(7) Choose the data mining techniques.

(8) Use algorithms to perform the task.

(9) Interpret the results.

(10) Deploy the model.

4. RESULTS

4.1 Problem Definition

In this initial step, the companies' needs were identified, alongside with management. In order to provide information that is consistent with the operation of the company, a monthly forecast for the next year was set as the desired output of the project. Management also determined that certain kinds of products need to have a more precise forecast and inventory policies, because of their difficulty in acquisition and warehouse handling. This was addressed in data analysis.

Another component of the problem definition was the decision of how to use data from 2020, due to the negative effect of pandemic on the market [11]. Statistical tests for outlier detection and graphical analyses were conducted for this matter, as it is described in section 4.3.2.

4.2 Data Collection

The company provided monthly unit sales from the previous four years, average unit cost and average unit sales price in the period. Relevant information for inventory costs calculation was gathered in meetings with management. Warehouse capacity and ratio of units per area per product was measured in-situ.

4.3 Data Analysis

This step was conducted prior to forecasting to ensure data gave relevant results and errors were minimized [8]. Ghiani (2013) proposed the next four steps to prepare data for a forecasting model [9].

4.3.1 Data cleansing

Twelve thousand SKUs were registered in the accounting software used by DAV Company. The first step was to discard products considered as discontinued: those whose price was lower than their cost, those that did not have sales in the time period to be analysed, and those that did not have sales in the previous year. Subsequently, those that had less than 3 data points were removed, considering 3 as the minimum amount of data to fit a forecasting model [47]. The final number of SKUs to be analysed was approximately 1 600.

4.3.2 Outlier identification

In a first step, five statistical tests commonly used in time series data were conducted, as explained by Kannan (2015), and previously used in Weatherford and Sheryl's (2015) forecasting project on hotel revenue management [16]. The tests conducted for total monthly sales were: Z-score, Modified Z-score, Tukey's Method, Median Absolute Deviation with deviation coefficients of 2 and 3 (MADe2, MADe3). Months 3 to 5 of 2020 were identified as outliers in more than one method, as it was expected due to the COVID19 Pandemic shutdowns; this is shown in Figure 3.

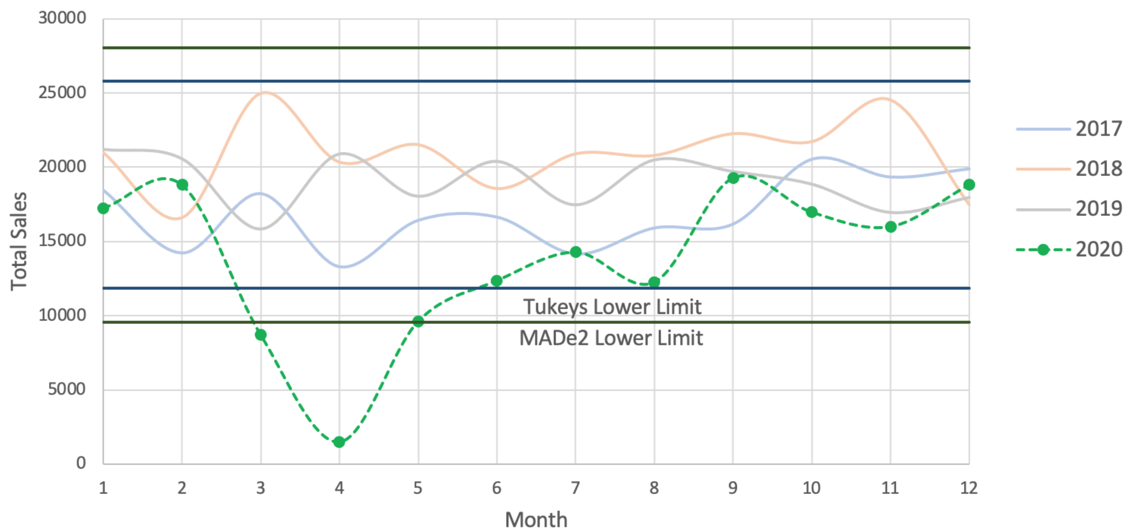

Figure 3. Total monthly sales of DAV Company, and outlier identification with Tukey's and MADe2 Methods

What should be done in these cases, according to Ghianni (2013), is to take out outliers, and replace them with an average value [9]. However, when conducting a deeper analysis, and in accordance with information given by management, it was determined that data from all 2020 was not representative of how the company started 2021, and how it expects to continue. This can be seen in Figure 4, where sales from 3 of the main 30 products' sales were plotted.

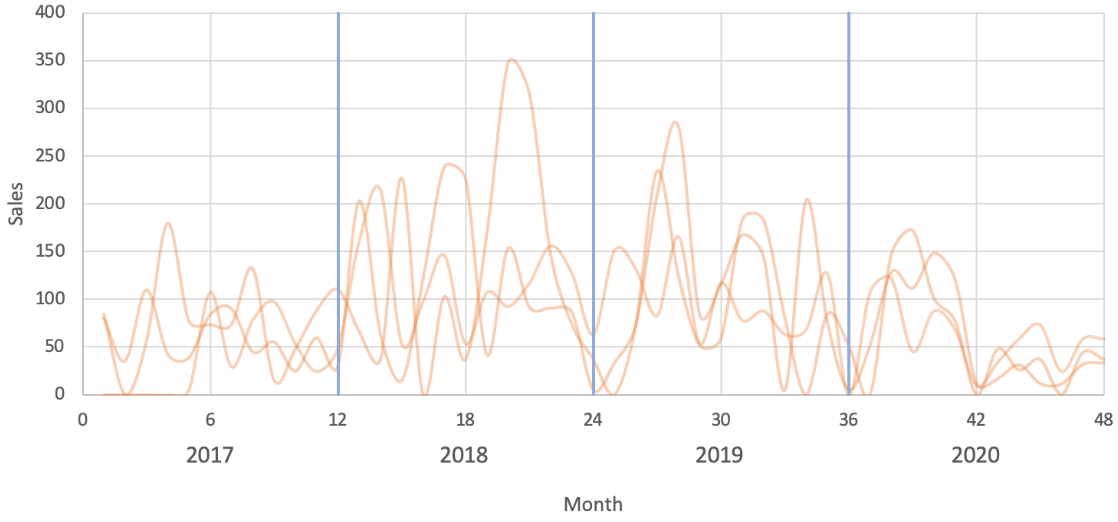

Figure 4. Sales of 3 of the top 30 SKUs. As it can be seen, all the last semester has lower sales than normal due to the pandemic.

As a result, data from 2020 were not used for forecasting, and instead, data from 2017 to 2019 was used to forecast 2021.

The final step was to take out outliers caused by sporadic data that was properly identified by the company as such.

4.3.3 Product classification

For the application of the ABC multi-criterion, DAV Company's management agreed on considering the criteria previously presented in [18] [19] [20] [21]. Given the data provided by the company, and reviewing common criteria used in multicriteria ABC presented by Castro et al. (2011) [22], a 4-criteria ABC analysis was used for classifying products:

(1) Total profit of the 3 historical years

(2) Profit coefficient of variation

(3) Average sales growth of the 3 historical years

(4) Product type

The first criterion addresses the classic measure for an ABC analysis, while the second one relates to demand variation. The third criterion represents the life cycle of the products, and the last one prioritizes products that are more difficult to handle in terms of inventory management. The first three criteria were calculated and normalized. The last criterion is qualitative and came from managerial input through the Analytic Hierarchy Process (AHP) method [23], which was then used to give weights to each criterion, as it was done in previous studies [18] [21] [22].

AHP requires the company to compare and rate each type of product, from a range from 1 to 9, according to their relative importance [23]. Each type of product is defined the by a combination of its unit of sale (units, meters or kg) and by the POS where the product is sold the most (there are 2 POS), for a total of six types of products. The matrix of the qualification of the types of products, with their calculated weights, is shown in Table 2.

Table 2. AHP Rates and Weights for Type of Product Criterion

Type of product	A	B	C	D	E	F	Weight
A	1	3	9	1	9	1	0.27
B	0.33	1	5	0.14	5	0.14	0.1
C	0.11	0.2	1	0.11	1	0.11	0.03
D	1	7	9	1	5	1	0.28
E	0.11	0.2	1	0.2	1	0.2	0.04
F	1	7	9	1	5	1	0.28

In order to obtain weights for each criterion, the same methodology was used, and it is presented in Table 3.

Table 3. AHP Rates and Weights for Criteria

Criteria	Profit	Coefficient of Variation	Sales Growth	Product Type	Weight
Profit	1	5	9	7	0.66
Coefficient of Variation	0.20	1	3	3	0.18
Sales Growth	0.11	0.33	1	3	0.10
Product Type	0.14	0.14	0.14	1	0.0.5

After obtaining values for each criterion, data was normalized, multiplied by each weight, and added; SKUs were sorted in descending order. SKUs that represent the 80% of the total sum, which are the most important ones based on the criterion selected [21], were considered for forecasting and inventory modelling: a total of 1583 SKUs were considered for the study.

4.3.4 Product aggregation

Products were aggregated based on their demand patterns [9], with unsupervised clustering. In order to do so, sales data must be normalized for all products, so aggregation is not influenced by the volume of sales of a product, but only by its pattern [27] [28]. Two unsupervised learning models were tested using Python: HAC and K-means. The first one had an initial forecasting MAPE of 48%, and the second had a MAPE of 37%. As a result, K-means was used as the model for clustering, and the initial forecasting error was subsequently improved only on K-means clusters. Clusters had between 1 and 58 SKUs (three clusters had demand values of cero). Parameters for the models and the average forecasting MAPE are presented in Table 4.

Table 4. Product Aggregation Models and Forecasting Results

Clustering Method	Reference for Parameter selection	Parameters	Number of clusters Method	Number of Clusters	Average Initial Forecast MAPE
HAC	Ruitenbeek (2019)	Distance: cosine. Linkage: Average	Maximum vertical distance in dendrogram	46	48%
K-means	Wang (2006)	Distance: Euclidean	Elbow Method	44	37%

4.4 Forecasting Model Selection & Fitting

First, the dataset was divided into a training set and test set in order to obtain realistic estimations of the forecasting errors. The years 2017 and 2018 were used as the training set, and the year 2019 was used as the test set. Each forecasting model had to generate a monthly forecast for 2021. The forecasting techniques applied to the clusters identified by the K-means model were developed entirely on Python. Multiple packages from the following libraries were used: pandas, numpy, matplotlib, sklearn, math, keras. croston, statsmodel. TSB croston was developed based on the code written by Vandeput (2020) [57].

The models specified in table 6 and their variations were run for all 44 clusters, and MAPE was calculated for 41 clusters with non-intermittent demand, MSE% was calculated for all 44 clusters.

In the first run, 13 clusters did not qualify as acceptable based on MAPE. To achieve acceptable error values for these clusters, the training set of each of these clusters was progressively shortened. In this way, the forecasts were progressively based on the most recent demand, which proved to improve the models' performance, even though the danger of overfitting increased [31].

After this modification, 6 clusters qualified as "very good", 14 as "good", and 16 as "moderate", according to Quality of forecasting previously presented in Table 1. Seven clusters did not come down from a MAPE of 30%, but neither did they rise from a MAPE of 35%, and were considered as acceptable once the predictions and tests were compared. A summary of these results is presented in Table 5.

Table 5. MAPE Distribution of non-intermittent demand clusters based on Table 1 Categories.

Quality of Forecasting	Average MAPE	Number of clusters
Very Good	5.1	6
Good	14.9	14
Moderate	24.5	16
Poor	32.9	7

As it can be seen in Table 6, Simple Exponential Smoothing was not the best fitted model for any cluster. Winters model demonstrated the best results in terms of the number of acceptable clusters, with 26 acceptable MAPE values. The ANN models demonstrated high performance as well, with 13 acceptable MAPE values. Nevertheless, within the ANN models, only the activation functions hyperparameter demonstrated to have significant variation in the forecasts error results. Therein, ANN models showed acceptable results with fewer hyperparameter variations in comparison with Winters models.

Table 6. Forecast results for clusters with non-intermittent demand, for each model.

Forecasting Method	Model Variations	Acceptabl e clusters	Average MAPE (%)	Average (MSE%)
Simple Exponential Smoothing	-	0	-	-
Double Exponential Smoothing (Holt)	Trend component: multiplicative or additive	1	22	29

Triple Exponential Smoothing (Winters)	Trend component: multiplicative or additive Seasonal component: multiplicative or additive Periods per season: from 2 to 12	26	16.5	18.8
Croston	Original, SBA, SBJ, TSB	1	25	27
Neural Networks	LSTM: Bidirectional, Vanilla CNN Activation Functions (LSTM, CNN): sigmoid, hyperbolic tangent and rectified linear unit	13	27.3	32.9

When comparing average MAPE and average MSE in table 6, the similarity of its magnitudes can be clearly seen. This means that using MSE% as the indicator for forecast precision for those where MAPE is not possible to calculate, might be a precise estimator. Regarding intermittent demand clusters, results are shown in Table 7. Cluster 12 had most of its data points with demand cero, inflating the error. Cluster 18 and cluster 44 present a much lower MSE%, close to that of non-intermittent demand models. As it was expected from the literature review, the Croston model fitted the best for most intermittent demand data series.

Table 7. Forecast results for clusters with intermittent demand.

Cluster	Products in Cluster	Best Fit Model and Variation	Average (MSE%)
Cluster 12	1	Croston – Original	150
Cluster 18	7	Winters - additive trend component, additiveseason component, 12 periods per season	13
Cluster 44	44	Croston - SBA	44

4.5 Inventory Model Selection

4.5.1 Inventory Cost Calculation

Inventory models take holding cost, h, and order cost k, as main cost inputs. Based on the steps followed in [13] for inventory cost calculation and considerations by Durlinger Consultancy Group [48], costs were calculated as follows:

4.5.1.1 k: Order Cost.

The average yearly hours used for operators preparing orders and its salaries were used to calculate order preparation cost. There were three delivery methods: by land, by air and by sea. Each delivery method had its own fixed cost. Considerations for product families were made based on delivery method, e.g. constructions materials are only delivered by land, while certain families are only imported by air. The estimated order cost calculated ranged from $26 to $93 for different product families.

4.5.1.2 h: Holding Cost.

For the cost of warehousing and space: storage space, warehouse rental rate, average participation of products in each of the two warehouses, and average space occupied by products were considered. Handling cost was calculated from average yearly hours spent by personnel in the warehouses and their salaries. Handling cost and basic services cost for each product is proportional to the average demand of each product. Opportunity cost was calculated based on an interest rate of 5.8% offered by a local bank [49]. Average unit cost ranged from $ 0.16 to $29.00.

4.5.2 Product Disaggregation

This step was done using the optimization model defined by equations (1), (2) and (3). The model was applied to each of the 12 forecasting points, for each of the 44 clusters. The model used order cost per SKU k_j which was calculated in the previous section, and the average of the demand λ_j was calculated from 2017-2019 historic demand. The minimum value between the lowest nonzero monthly demand and the average monthly demand was used as the minimum order size a_j. A maximum value of order b_j was not considered for the model, as this was not a restriction for the company. The model was run with GRG Nonlinear Solver in MS Excel. The result was the disaggregated forecast for the 1583 SKUs.

4.5.3 Inventory Model Selection

Based on the inventory model selection chart presented in Figure 1, the following characteristics were taken into account in order the select the appropriate inventory model:

(1) According to Taha (2012) [50], products with a coefficient of variation > 0.2 for its demand, can be considered as stochastic or unknown. This was the case for all the 1583 SKUs.

(2) DAV Company has an accounting system that allows a continuous inventory review.

(3) Stockout cost was unknown by the company.

(4) Stockout effects depend on the number of units, according to management experience.

Thus, the Q, R with Service Type 2 was selected for all SKUs. Gallman & Belvedere (2010) reviewed a series of inventory management studies in different retailers and distributors, most of them using a service level of $\beta = 98\%$ [51]. Using this β and the demand parameters and costs previously described, the Q, R model was calculated in MS Excel. Order quantities Q and reorder points R for all 99% of SKUs were obtained after 5 iterations, and after 160 iterations for 0.5% SKUs. For the remaining 0.5%, the model did not converge, but the difference between the last iterations was less than 0.1% of the average demand, so an acceptable sub optimal solution was reached.

4.6 Forecasting & Inventory Model Deployment

DAV Company's management was closely involved during the whole project. Results were presented and explained, ensuring the understanding of product demand similarity based on the cluster they belong to. An explanation of the forecasting error and how to understand it was highlighted, and inventory variables Q and R and how to use them were described. Results were delivered in a .xlsx format containing a table with 1583 rows, one for each SKU, with columns: cluster, best fit model, forecast for 12 months, Q, and R.

(1) Cluster

(2) Best fit model

(3) Forecast in units for the next 12 months

(4) Order quantity Q

(5) Reorder Point R

5. DISCUSSION

Results of the forecasting methods demonstrated that Winters models are a suitable alternative to forecast irregular demand due to its broad range of model variants, each one resulting from the combination of the election of the type of seasonal component (additive or multiplicative), trend component (additive or multiplicative) and number of periods for the season (from 2 to 12 periods). The number of clusters that were able to be forecasted with MAPE values below 30% using the Winters models, is the highest among all the models, with a total of 27 clusters. The mean MAPE for the Winters model is 16.5%, which implies that the central tendency of most of the MAPE errors was in the acceptable range [9]. In the case of ANN models, the results demonstrated to be less effective in comparison with Winters, with 13 clusters in an acceptable MAPE range. Nevertheless, only one hyperparameter was changed to obtain the forecasts, therefore, ANN models' performance is acceptable. The results obtained in this study are significantly different from those demonstrated in a study conducted by Jurczyk et al. [2016], where the ANN models proved to have better results in comparison with traditional forecasting models (including Winters) [39].

The reason for this difference lies in a better ANN mode preparation [39]. For example, the functional sequence of the network learning errors using Levenberg-Marquardt algorithm determined the number of epochs to employ [39]. Ultimately, the best learning algorithm to use in the network was determined through a linear regression analysis of the entire dataset [39]. In the present study, the hyperparameters were determined through various iterations and literature standards. Additionally, other studies have shown the potential of ETS models (error, trend, seasonal) like Winters in terms of SMAPE, by outperforming models such as ARIMA, KNN, and having similar results with simple RNN [58].

The worst performance was demonstrated by the simple exponential smoothing model, which did not reach any MAPE acceptable value for any cluster. In the case of double exponential smoothing and Croston's models, the performance was poor as well, with only one acceptable forecast for one cluster in each one. Poor performance of Croston model can be seen un multiple studies, such as one conducted in the aircraft spare parts industry where the Croston model did not achieved best forecasting model for any of the sample of 30 parts [40]. Additionally, a literature review done by Xu et al. (2012) demonstrated that Croston model's performance was below other forecasting models, specifically weighted moving average [32]. In this study the error measure was MSE [40]. Nevertheless, simple models cannot be ignored and replaced for other more complex arbitrarily, as they continue to be relevant for some products, as shown in most studies [13] [17] [27].

Three clusters had zero values in their datasets. For these clusters, MAPE could not be determined since the output would have been indeterminate. For these clusters the forecasting models that yield the smallest MSE values were considered as the best. Comparing MSE% and MAPE, indicated MSE% can be used for measuring forecast accuracy, but the number of zeros in the time series should be considered. MSE% expresses how close each data point is to the validation set [6]. Therefore, mean MSE% values for Winters model showed that these forecasts are closer to the test set, followed by the ANN mean MSE values. It must be emphasised that the models used for the seven clusters that did not achieve acceptable MAPE values must not be generalized for future forecasting sales. Given the large overfitting component, these models are of exclusive use for the 2021 forecast.

The inventory system used for finding the optimum Q, R policy was based on a type 2 service level. All the parameters involved in the calculations were provided by DAV company using the value of beta, which was obtained from theliterature [51]. The demand parameter was estimated using the disaggregated forecasted demand of the clusters. Convergence arrived after five iterations for 99% of SKUs. The approximate optimal policy for the remaining SKUs that did not converge can be considered useful for DAV Company since the difference is less than 0.1%. One of the main reasons convergence was not achieved is because every cluster was made from a highly variable number of SKUs (from 1 to 60 SKUs conformed every cluster). This, in turn, caused the forecasting models to be unable to capture certain variability present in the clusters. Thus, a very wide range of units were forecasted (from zero to six million units). Ultimately, the large differences in demand forecasts represented a limitation for the convergence in the Q, R optimal policy.

A major limitation of the study was the inability to frequently visit DAV company facilities given the COVID-19 pandemic. This resulted in a limited supply of information about products distribution and sales flow, personnel workflow, the inability to visit the warehouse located in Ambato city, and other important operational insights. Another limitation of this study was, as mentioned before, that the ANN models' hyperparameters were tuned in a standard and iterative way, where only past data was considered for model training. Several studies have shown that grid search, linear regression and simulation can improve significantly the ANN forecast results [62][39][40]. Other studies have shown that ANN models that implement more than one input feature get more accurate results since the model's training is greater [38][71]. These techniques and considerations can be implemented in future studies to obtain more accurate and realistic ANN forecasts. Ultimately, several more advanced model evaluation methods, besides the classical training and testing split could provide better results [72]. For instance, walk forward validation is a state-of-the-art method in which a minimum number of observations must be decided to train the model as well as a sliding window to include all data or just the most resent observations [72]. This technique trains the model iteratively. The model has the benefit of demonstrating more realistically how the chosen model and parameters will perform in practice [72].

6. CONCLUSION

This work demonstrated the appropriate implementation of data analytics in traditional industrial engineering disciplines, such as forecasting and inventory management. A forecast for the next year could be made with the help of multidisciplinary techniques such as the multi criterion ABC, AHP Methodology, Unsupervised clustering, classic forecasting and inventory models, and the use of Neural Networks on forecasting techniques.

Montgomery’s Forecasting Process [8] and Shmueli’s Data Mining Procedure [31] were systematically used and integrated in a single project to accomplish the project’s objectives.

Valuable insights and recommendations could be delivered to the company, which would have not been possible with empirical analysis previously done by the company. As a result, the company has expressed interest in storing data relevant to continue and improve demand planning and inventory management. It is important to highlight DAV Company’s opening and involvement in the project. Forecasting needs the input from the expert.

As it was seen during this study, MAPE error is not always the proper indicator of the best fitted model. A trade-off between minimizing the error and approximating the forecast pattern to that of the real test set has to be taken into account when deciding the model to be used. On the other hand, further studies are recommended in forecasting error measures.

The use of Python and related libraries showed great potential for tuning the model parameters and hyperparameters in an automated and flexible way. Coding allows deeper visualization of the different characteristics and components of the forecasting models as well, which in turn provides a better understanding of the whole forecasting processes. This allows investigators to take more informed and effective decisions regarding data pre-processing, model evaluation and forecasting, which in turn can be combined with statistical techniques to find the best combination of techniques, parameters and hyperparameters.

Additionally, the present study demonstrated how modern forecasting techniques involving neural networks can successfully forecast with smaller errors in comparison to traditional forecasting models. Few studies demonstrated Python’s potential as the main environment to develop the forecasting results [38][71]. nor did they developed the process of

SKU aggregations for forecasting and disaggregation to develop the inventory control using statistical and optimization models that considers minimizing costs at individual SKU level. In [19] and [13], only main SKUs were forecasted individually, the rest were aggregated based on graphical methods and not disaggregated. In [28] and [24], clustering and ARIMA was used for aggregation respectively, and an average function based on historic demand was used to disaggregate forecasts. On the other hand, [53] disaggregated forecasts based on the optimization model, but aggregation was based on predefined product families. None of the studies mentioned in this paper used clustering or other statistical method for aggregation and an optimization model for disaggregation.

Finally, the study was conducted in a company located in Ecuador where techniques and practices involving forecasting and inventory for small companies are generally done in an empirical way [53] [66] [67]. Therefore, this study paves the way for these types of companies to integrate its operations with engineering theory to become more efficient and grow in an economically sustainable way. This is especially relevant in the current challenging economic environment created by the COVID-19 Pandemic.

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